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Resource Allocation in NOMA Networks: Convex Optimization and Stacking Ensemble Machine Learning

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ABSTRACT This article addresses the joint power allocation and channel assignment (JPACA) problem in uplink non-orthogonal multiple access (NOMA) networks, an essential consideration for enhancing the performance of wireless communication systems. We introduce a novel methodology that integrates convex optimization (CO) and machine learning (ML) techniques to optimize resource allocation efficiently and effectively. Initially, we develop a CO-based algorithm that employs an alternating optimization strategy to iteratively solve for channel and power allocation, ensuring quality of service (QoS) while maximizing the system's sum-rate. To overcome the inherent challenges of real-time application due to computational complexity, we further propose a ML-based approach that utilizes a stacking ensemble model combining convolutional neural network (CNN), feed-forward neural network (FNN), and random forest (RF). This model is trained on a dataset generated via the CO algorithm to predict optimal resource allocation in real-time scenarios. Simulation results demonstrate that our proposed methods not only reduce the computational load significantly but also maintain high system performance, closely approximating the results of more computationally intensive exhaustive search methods. The dual approach presented not only enhances computational efficiency but also aligns with the evolving demands of future wireless networks, marking a significant step towards intelligent and adaptive resource management in NOMA systems.

INDEX TERMS non-orthogonal multiple access (NOMA), machine learning (ML), quality of service (QoS), joint power allocation and channel assignment (JPACA), resource allocation, convex optimization (CO), stacking ensemble method.

I. INTRODUCTION

With the continuous advancement of wireless communication networks, devising effective and efficient strategies for resource allocation in non-orthogonal multiple access (NOMA) networks is critical. Efficient network operation requires the ability to handle both predictable and unpredictable changes in conditions and user behavior. A promising mechanism to address these complex challenges is machine learning (ML), which offers the potential to dynamically and adaptively optimize resource allocation, i.e., power allocation (PA) and channel assignment (CA) [1]. Recent years have seen steady research interest in exploring ML's potential in NOMA networks. For example, deep reinforcement learning has been applied to optimize joint beamforming and PA in multi-user MIMO-NOMA systems, demonstrating significant improvements in system performance by leveraging machine learning (ML) techniques to address complex resource allocation challenges [2]. However, despite these advancements, a notable research gap exists in the application of ML to the joint optimization of PA and CA specifically in uplink NOMA networks. Most existing studies focus on downlink scenarios or address PA and CA separately, often relying on conventional optimization techniques that may not scale well in dynamic and complex environments. Moreover, while there has been significant progress in applying convex optimization (CO) and ML techniques independently for resource allocation, there is a lack of comprehensive studies that integrate these approaches to address the computational challenges and dynamic nature of uplink NOMA systems [3]. To address this gap, we propose a stacking ensemble approach, integrating convolutional neural network (CNN), feed-forward neural network (FNN), and random forest (RF) models. By capitalizing on the strengths of each model in capturing spatial features, non-linear relationships, and robust decision boundaries, the proposed ensemble achieves superior performance in solving the joint power allocation and channel assignment (JPACA) problem for uplink NOMA. Our results demonstrate significant improvements in sum rate and computational efficiency, alongside enhanced adaptability to dynamic network conditions. The effectiveness of the proposed approach and its performance gains are assessed through extensive simulations.

II. RELATED WORK

The inception of NOMA technology marked a pivotal development in wireless communication, aiming to meet the escalating demand for higher spectral efficiency and improved user multiplexing capabilities. Initial research focused on optimizing resource allocation mechanisms such as PA and CA to enhance system performance. As the field progressed, integrating ML and advanced optimization techniques into NOMA became a crucial area of investigation. For instance, [1] presented an ML-based localization method for NOMA in shadowed visual light communication systems, highlighting ML‘s potential to navigate complex optimization landscapes. Similarly, [2] utilized deep reinforcement learning to optimize joint beamforming and PA in multi-user MIMO-NOMA systems. This approach demonstrates significant improvements in system performance by leveraging ML techniques to address the complex resource allocation challenges in NOMA networks. Focusing on uplink NOMA scenarios, the JPACA problem emerged as a critical challenge, necessitating innovative approaches for efficient resource management. Contributions such as [4] and [5] proposed algorithms to enhance the energy efficiency and security of NOMA systems, respectively. Further explorations into grant-free NOMA systems by [6] and wireless power transfer in [7] reflected the wide spectrum of applications and challenges within NOMA resource allocation. Additionally, recent studies have emphasized the practical implications of imperfect successive interference cancellation (SIC) due to channel estimation errors and hardware impairments, which are important for realistic implementations of NOMA. For instance, Prakriya explored the performance of multiuser uplink underlay NOMA networks with channel knowledge, highlighting the impact of imperfect SIC on system performance [8]. Similarly, Gupta and Prakriya examined spectrally-efficient uplink underlay multiuser networks with imperfect SIC, providing insights into how residual interference can affect network efficiency [9]. Further, The authors in [10] investigated CSI-based power control and NOMA/orthogonal multiple access (OMA) switching for uplink underlay networks with imperfect SIC, demonstrating the necessity of accounting for imperfect SIC in power control strategies. To address the JPACA challenge, various methodologies have been introduced to optimize resource distribution in uplink NOMA. Techniques centered on spectrum and energy efficiency, utilizing graph-based methods and considering spectral efficiency metrics, are presented in works such as [11] and [12]. These contributions are vital for understanding established strategies and identifying constraints in JPACA optimization. Despite technological advancements, there remains a void in devising computationally efficient algorithms that can deliver near-optimal solutions for JPACA in uplink NOMA. Our investigation aims to fill this gap by proposing an innovative algorithm that integrates CO with a stacking ensemble ML technique, striving to enhance both computational efficiency and service quality. This initiative is inspired by insights from [13], which explores user fairness and quality of service (QoS)-aware resource allocation, and [14], which emphasizes the need for adept algorithms in NOMA frameworks. A comparative analysis of existing literature is provided in Table 1. This table highlights the significant differences between our work and previous studies, demonstrating the unique contributions and advancements of our approach.

Unlike previous approaches, our proposed method leverages ML‘s predictive capabilities to anticipate optimal allocation strategies under varying network conditions, addressing the static nature and lack of real-time adaptability of existing methods. By adopting a stacking ensemble ML approach, we synergize the strengths of individual ML models, such as CNNs for spatial feature extraction and RFs for robust decision boundaries. This integration enhances computational efficiency and improves the quality of service by adapting more effectively to network dynamics. Building upon and integrating the contributions from related works, this study presents a comprehensive solution to the JPACA problem, addressing the computational challenges and performance requirements of modern wireless networks. Our proposed method contributes to the ongoing development of efficient and effective NOMA systems by leveraging the strengths of both ML and CO in a novel approach to resource allocation.

A. MOTIVATIONS AND CONTRIBUTIONS OF THIS WORK

JPACA optimization in NOMA-based wireless networks is a critical area of research. Current research primarily focuses on iterative algorithms. However, another promising approach to JPACA optimization in NOMA-based wireless networks is the use of ML. In this study, we first derive the closed-form rate of each user by considering the effects of CA and PA in multi-user uplink communication in a cellular wireless network. Subsequently, we construct an optimization framework to maximize the sum rate

TABLE 1. Comparative analysis of existing literature.

Reference	Focus	Techniques	Key Contributions	Significant Differences
Gupta and Prakriya (2022) [10]	Power control and NOMA/OMA switching in uplink underlay networks	Imperfect SIC, Power Control	Investigated CSI-based power control and NOMA/OMA switching with imperfect SIC	Focuses on power control; lacks ML and CO for JPACA.
Affan et al. (2023) [1]	ML-based localization in NOMA for VLC systems	ML-based Localization	Introduced ML for localization in shadowed VLC systems	Focused on localization; does not address uplink NOMA.
Cui et al. (2022) [4]	Energy-efficient resource allocation for downlink NOMA	Energy-efficient Algorithms	Enhanced energy efficiency in downlink NOMA systems	Focuses on downlink NOMA; not on uplink JPACA or ML techniques.
Dang et al. (2022) [5]	Secure performance in aerial RIS-NOMA systems	Deep Neural Networks	Investigated secure performance in RIS-NOMA using deep learning	Focuses on security; does not integrate JPACA with CO.
Tran et al. (2022) [6]	Power control and subchannel selection in grant-free NOMA for URLLC	Reinforcement Learning	Introduced reinforcement learning for power control and subchannel selection	Specific to grant-free NOMA and URLLC; not on uplink JPACA.
Goktas and Ding (2022) [7]	Wireless power transfer in NOMA systems	Wireless Power Transfer	Proposed a wireless power transfer-assisted NOMA transmission scheme	Focuses on power transfer; not on JPACA optimization or ML techniques.
Zhai and Du (2018) [11]	Spectrum-efficient resource management for multi-carrier NOMA	Graph-based Methods	Spectrum-efficient resource management using graph-based methods	Spectrum efficiency using graph methods; lacks ML or CO for JPACA.
Zeng et al. (2019) [12]	Spectral and energy-efficient resource allocation for multi-carrier NOMA	Spectrum and Energy Efficiency	Proposed spectral and energy-efficient resource allocation	Spectrum and energy efficiency; does not combine ML and CO for JPACA.
Gupta and Prakriya (2024) [8]	Multiuser uplink underlay NOMA with channel knowledge	Imperfect SIC, Channel Knowledge	Examined imperfect SIC on multiuser uplink underlay NOMA	Focuses on imperfect SIC; lacks ML and CO.
Gupta and Prakriya (2024) [9]	Spectrally-efficient uplink underlay multiuser NOMA with imperfect SIC	Imperfect SIC, Spectral Efficiency	Analyzed spectrally-efficient uplink underlay NOMA with imperfect SIC	Focuses on imperfect SIC; lacks ML for JPACA optimization.
This paper	JPACA in Uplink NOMA Networks	CO, Stacking ML	Integrates CO with stacking ensemble ML for JPACA	Combines CO with ML for JPACA in uplink NOMA networks.

for all users by optimizing JPACA. Given that the sum-rate maximization problem is a mixed-integer non-convex problem, a significant challenge is obtaining a comprehensive solution. To overcome this challenge, we present a two-stage CO methodology that systematically handles one unknown variable while retaining the other as fixed. We also present an efficient algorithm, based on supervised ML, to solve the joint optimization problem. The main motivation is to use supervised ML to address the high computation latency by converting the joint optimization problem into a regression problem. Overall, supervised ML has two primary stages: (1) the pre-processing phase and (2) the post-processing phase. In the former phase, an ML model is trained using labeled datasets associated with channel state information (CSI). In the latter phase, the trained ML model is used to identify the optimal parameters, without the need to solve a CO-based algorithm, thereby reducing computation latency. Major contributions and novelties of the present study can be summarized as follows:

- Aiming to maximize the sum-rate while guaranteeing QoS requirements, we formulate a novel application of the JPACA problem for uplink NOMA-based wireless communication networks.
- To solve the problem, we propose a two-stage CO algorithm that iteratively optimizes one variable while keeping the others fixed, allowing us to achieve near-optimal solutions with low complexity.
- We introduce an ML-based approach to further enhance the computational efficiency of the joint optimization algorithm. By transforming the problem into a regression problem and using supervised learning, we approximate the optimal solution, significantly reducing computation time without sacrificing system performance.
- To demonstrate the effectiveness and efficiency of our proposed algorithms and compare them with state-of-the-art methods, we conduct extensive simulations. The results show that our proposed algorithms can achieve superior performance with lower computational complexity.

B. ORGANIZATION

The remainder of this paper is structured as follows. Section II introduces the related work. Section III presents the system model and problem formulation. In Section IV, we describe the proposed CO-based method. Section V discusses the ML-based method for enhancing computational efficiency. Section VI reports simulation results and computational complexity analysis, focusing on comparing the proposed method to other available approaches. Section VII

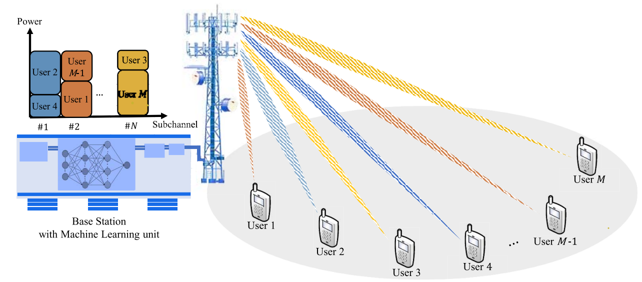

FIGURE 1. System model of a NOMA uplink with ML-based resource allocation.

outlines potential future applications. Finally, Section VIII concludes the paper.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

In this study, we consider a system with N subchannels and M users, where each subchannel can be assigned to one or more users due to the limited number of channels available ($M \geq N$). In this access scheme, NOMA with multiple users in each subchannel is used (see Fig. 1).

The received signal at the base station (BS) in the n-th subchannel is represented by Eq. (1):

$$y_n = \sum_{m=1}^{M} h_{m,n}\sqrt{p_m} x_{m,n} s_m + w_n, \tag{1}$$

where s_m is the signal transmitted by the m-th user with unit power and $\mathbb{E}[|s_m|^2] = 1$ for all $m \in 1, \dots, M$. The binary variable $x_{m,n}$ denotes whether the m-th user occupies the n-th subchannel ($x_{m,n} = 1$) or not ($x_{m,n} = 0$). The corresponding transmit power is denoted by p_m, while $h_{m,n}$ represents the gain of the n-th subchannel for the m-th user. The received white Gaussian noise in the n-th subchannel, which follows the distribution of $\mathcal{CN}(0, \sigma^2)$, is denoted by w_n. Assuming successive interference cancellation (SIC) in the uplink NOMA communication, the signal-to-interference-plus-noise ratio (SINR) of the m-th user in the n-th subchannel is given by [15] (see Eq. (2)):

$$\mathrm{SINR}_{m,n} = \frac{x_{m,n} p_m h_{m,n}}{\sum_{i=m+1}^{M} x_{in} p_i h_{in} + \sigma^2 B}, \tag{2}$$

where B is the bandwidth of each subchannel, and For the last user $m = M$, there is no interference from other users, but the noise term remains:

$$\mathrm{SINR}_{M,n} = \frac{x_{M,n} p_M h_{M,n}}{\sigma^2 B}, \tag{3}$$

According to Eq. (2), the achievable data rate of the m-th user under the NOMA protocol considering SIC is given by Eq. (4):

$$r_m = \sum_{n=1}^{N} B \log_2\left(1 + \mathrm{SINR}_{m,n}\right), \tag{4}$$

and the sum rate of all users assigned to the n-th subchannel is given by Eq. (5):

$$\begin{aligned} r_n &= \sum_{m=1}^{M} B \log_2\left(1 + \mathrm{SINR}_{m,n}\right) \qquad (5) \\ &\overset{(a)}{=} B \log_2\left(1 + \frac{\sum_{m=1}^{M} x_{m,n} p_m h_{m,n}}{\sigma^2 B}\right), \end{aligned}$$

where (a) holds since the terms inside the brackets in the sum rate expression form a telescoping product. To account for the impact of the downlink control channel's latency and performance, we introduce additional constraints in the optimization process. These constraints ensure that the control signaling overhead does not adversely affect the performance of the resource allocation strategies. Specifically, we include constraints for control channel latency and bit error rate (BER):

$$\begin{aligned} &L_{\mathrm{control}} \leq L_{\max}, \\ &\mathrm{BER}_{\mathrm{control}} \leq \mathrm{BER}_{\max}. \end{aligned}$$

These constraints ensure that the latency and reliability of the downlink control channel are within acceptable limits, supporting the dynamic and adaptive nature of the proposed PA and CA schemes.

B. PROBLEM FORMULATION

In this study, we aim to maximize the sum rate of the users through the JPACA problem. This problem can be expressed as shown in Eq. (6):

$$\begin{aligned} (\mathcal{P}): \quad & \max_{\boldsymbol{x},\boldsymbol{p}} \sum_{n=1}^{N} r_n && && \text{(6a)} \\ \text{s.t.} \quad & p_m \leq p_m^{\max}, && \forall m \in \{1, \dots, \mathcal{M}\}, && \text{(6b)} \\ & r_m \geq R_m^{\min}, && \forall m \in \{1, \dots, \mathcal{M}\}, && \text{(6c)} \\ & \sum_{n=1}^{N} x_{m,n} = 1, && \forall m \in \mathcal{M}, && \text{(6d)} \\ & \sum_{m=1}^{M} x_{m,n} = A, && \forall n \in \mathcal{N}, && \text{(6e)} \\ & x_{m,n} \in \{0, 1\}, && \forall m \in \mathcal{M}, n \in \mathcal{N}, && \text{(6f)} \\ & L_{\mathrm{control}} \leq L_{\max}, && && \text{(6g)} \\ & \mathrm{BER}_{\mathrm{control}} \leq \mathrm{BER}_{\max}, && && \text{(6h)} \end{aligned}$$

where $\boldsymbol{x} = [x_{11}, x_{12}, \dots, x_{M,N}]^T$ and $\boldsymbol{p} = [p_1, p_2, \dots, p_M]^T$ represent the CA matrix and the transmit power vector, respectively. Constraints (6b) and (6c) ensure that the corresponding transmit power does not exceed the maximum transmit power, i.e., $p_m^{\max}$, and guarantee the QoS for each individual user, where $R_m^{\min}$ is the minimum rate requirement for the m-th user. Additionally, constraint (6e), ensures each user is assigned to at least one subchannel while respecting the maximum capacity, A, of users per subchannel. Constraints (6b) and (6c) guarantee the transmit power does not exceed the maximum allowed and that the QoS requirements are met, respectively. This allows efficient resource utilization by ensuring each subchannel is fully used but prevents overloading with more users than it can handle.

IV. CONVEX OPTIMIZATION-BASED METHOD

In this section, we present a CO-based algorithm for the multi-user NOMA system, which concurrently addresses both CA and PA problems. In the optimization problem ($\mathcal{P}$), we identify that constraints (6d) to (6f) pertain only to the CA variable x. Meanwhile, variables p_m and r_m in (6a) and (6b) are dedicated exclusively to controlling the transmit power and the QoS for each user. Given this observation, we employ the alternating optimization strategy to address the challenge delineated in problem ($\mathcal{P}$). To this end, we iteratively optimize p_m and $x_{m,n}$ by addressing the following two related sub-problems:

Sub-Problem 1: CA aims to maximize the sum rate of all users in the NOMA system. The problem is formulated as an integer linear programming problem, which can be efficiently solved using standard optimization techniques or heuristics.

Sub-Problem 2: PA with QoS consideration, The PA problem focuses on maximizing the total rate while considering the QoS for each user. The problem is formulated as a CO problem, with due consideration of the minimum required rate for each user ($R_m^{\min}$). To solve this problem, we propose using the interior point method, which is well-suited for solving CO problems and can provide an optimal solution for the PA problem with the QoS constraint.

In what follows, we provide an overview of the proposed method and the sub-problems it addresses.

A. SUB-PROBLEM 1: CA OPTIMIZATION

Given the conditions for power and QoS, we can reformulate the optimization problem ($\mathcal{P}$) as a CA problem:

$$
\begin{aligned}
(\mathcal{P}1):\quad & \max_{\boldsymbol{x}} \sum_{n=1}^{N} r_n && (7a)\\
\text{s.t.}\quad & \sum_{n=1}^{N} x_{m,n} = 1, \qquad \forall m \in \mathcal{M}, && (7b)\\
& \sum_{m=1}^{M} x_{m,n} = A, \qquad \forall n \in \mathcal{N}, && (7c)\\
& x_{m,n} \in \{0,1\}, \qquad \forall m \in \mathcal{M}, n \in \mathcal{N}. && (7d)\\
& L_{\text{control}} \le L_{\max}, && (7e)\\
& \text{BER}_{\text{control}} \le \text{BER}_{\max}. && (7f)
\end{aligned}
$$

To solve problem ($\mathcal{P}1$), we initially relax the binary constraints in Eq. (7d) by allowing variables $x_{m,n}$ to assume continuous values within the interval [0, 1]. This relaxation transforms the problem into a linear and CO problem, which can then be efficiently solved using the dual method. By incorporating the Lagrange function into the problem ($\mathcal{P}1$), we can formulate the Lagrangian as shown in Eq. (8):

$$
\begin{aligned}
\mathcal{L} = & \sum_{n=1}^{N} r_n \\
& + \sum_{m=1}^{M} \lambda_m \left(\sum_{n=1}^{N} x_{m,n} - 1 \right) \\
& + \sum_{n=1}^{N} \left(\alpha_n \left(\sum_{m=1}^{M} x_{m,n} - A \right) \right) \\
& + \sum_{n=1}^{N} \sum_{m=1}^{M} \left(\beta_{m,n} x_{m,n} + \gamma_{m,n}(1 - x_{m,n}) \right) \\
& + \sum_{m=1}^{M} \nu_m (L_{\text{control}} - L_{\max}) \\
& + \sum_{m=1}^{M} \mu_m (\text{BER}_{\text{control}} - \text{BER}_{\max}), \qquad (8)
\end{aligned}
$$

where λ_m, α_n, $\beta_{m,n}$, $\gamma_{m,n}$, ν_m, and μ_m are the dual variables associated with the constraints in Eq. (7b), (7c), (7d), (7e), and (7f), respectively. The Karush-Kuhn-Tucker (KKT) conditions for problem ($\mathcal{P}1$) are presented as shown in Eq. (9):

$$
\begin{aligned}
& \frac{p_m}{\kappa_n} + \lambda_m = \gamma_{m,n} - \beta_{m,n} - \alpha_n \\
& \qquad + \nu \frac{\partial L_{\text{control}}}{\partial x_{m,n}} + \mu \frac{\partial \text{BER}_{\text{control}}}{\partial x_{m,n}}, && (9a)\\
& \sum_{n=1}^{N} x_{m,n} = 1, && (9b)\\
& \sum_{m=1}^{M} x_{m,n} = A, && (9c)\\
& \beta_{m,n} x_{m,n} = 0, && (9d)\\
& \gamma_{m,n} \left(1 - x_{m,n}\right) = 0. && (9e)
\end{aligned}
$$

where κ_n is a new variable, remaining constant for each user m, introduced as in Eq. (10):

$$
\kappa_n = (\ln 2) \left(\sum_{m=1}^{M} x_{m,n} p_m h_{m,n} + \sigma^2 B \right). \qquad (10)
$$

Based on Eq. (9d) and (9e), for a given sub-channel n, we can draw the following conclusions:

- If $\beta_{m,n} = 0$ and $\gamma_{m,n} \ge 0$, then $x_{m,n} = 1$.
- If $\beta_{m,n} \ge 0$ and $\gamma_{m,n} = 0$, then $x_{m,n} = 0$.

These conditions imply that the right-hand side of Eq. (9a) should be maximized when $x_{m,n} = 1$. Furthermore, from Eq. (9c), it is evident that only A users will have $x_{m,n} = 1$. Therefore, A users with the highest values of:

$$
\frac{p_m h_{m,n}}{\kappa_n} + \lambda_m + \mu \frac{\partial L_{\text{control}}}{\partial x_{m,n}} + \nu \frac{\partial \text{BER}_{\text{control}}}{\partial x_{m,n}}
$$

Algorithm 1 Proposed Algorithm for Optimal CA

1: **Initialization**: $\lambda_m, \mu, \nu, \forall m \in \mathcal{M}$
2: **while** Not converged **do**
3: Calculate κ_n by solving (12) using bisection method.
4: Update channel assignment based on (11).
5: Update λ_m, μ, and ν using the gradient descent method.
6: **end while**
7: **Output**: Optimal channel assignment $x^{\star}_{m,n}$

should be assigned $x_{m,n} = 1$. This leads to the following optimal solution for $x_{m,n}$:

$$x^{\star}_{m,n}(\kappa_n, \lambda_m, \mu, \nu) = \begin{cases} 1, & \text{if } m \in \mathcal{M}_A \\ 0, & \text{otherwise} \end{cases}, \tag{11}$$

where the set $\mathcal{M}_A$ denotes the indices of the A users with the highest values of $\frac{p_m h_{m,n}}{\kappa_n} + \lambda_m + \mu \frac{\partial L_{\text{control}}}{\partial x_{m,n}} + \nu \frac{\partial \text{BER}_{\text{control}}}{\partial x_{m,n}}$. To ascertain the value of κ_n, we combine Eq. (10) and (11), which gives:

$$\kappa_n = (\ln 2) \left(\sum_{m=1}^{M} x^{\star}_{m,n}(\kappa_n, \lambda_m, \mu, \nu) p_m h_{m,n} + \sigma^2 B \right). \tag{12}$$

With a constant λ_m, as κ_n increases, users with lower $p_m h_{m,n}$ values may achieve higher $\frac{p_m h_{m,n}}{\kappa_n} + \lambda_m + \mu \frac{\partial L_{\text{control}}}{\partial x_{m,n}} + \nu \frac{\partial \text{BER}_{\text{control}}}{\partial x_{m,n}}$ values. Consequently, the value of $\sum_{m=1}^{M} x^{\star}_{m,n}(\kappa_n, \lambda_m, \mu, \nu) p_m h_{m,n}$ decreases, indicating that the right-hand side of Eq. (12) diminishes as κ_n increases. Since the left side of Eq. (12) increases with κ_n and the right side decreases with κ_n, a unique value of κ_n can be identified using the bisection method. Thereafter, the value of λ_m can be determined using the gradient method [16]. By iteratively optimizing the primary variable $x_{m,n}$ and the secondary variables λ_m, μ, and ν, the optimal subchannel allocation is achieved. The proposed optimal CA, along with the dual approach used to achieve this allocation, is thoroughly detailed in Algorithm 1.

B. SUB-PROBLEM 2: PA OPTIMIZATION

In sub-problem 2, the given CA, i.e., $x_{m,n}$, reduces $(\mathcal{P})$ to an optimization problem with PA only (see Eq. (13)):

$$(\mathcal{P}2): \quad \max_{\mathbf{p}} \; B \log_2 \left(1 + \frac{\sum_{m=1}^{M} p_m h_m}{\sigma^2 B} \right) \tag{13a}$$

$$\text{s.t.} \quad p_m \le p_m^{\max}, \quad \forall m \in \{1, \dots, M\}, \tag{13b}$$

$$r_m \ge R_m^{\min}, \quad \forall m \in \{1, \dots, \mathcal{M}\}, \tag{13c}$$

$$L_{\text{control}} \le L_{\max}, \tag{13d}$$

$$\text{BER}_{\text{control}} \le \text{BER}_{\max}, \tag{13e}$$

where $h_m = \sum_{n=1}^{N} x_{m,n} h_{m,n}$ is the subchannel used by the m-th user. In this study, we assume that the BS knows h_m perfectly. The BS aims to maximize the SINR of each user using a PA vector $\mathbf{p} = [p_1, \dots, p_M]$ subject to the constraint in Eq. (13c). As each user can be assigned to only one subchannel (according to Eq. (6d)), Eq. (13c) can be rewritten as shown in Eq. (14):

$$r_m = B \log_2 \left(1 + \frac{p_m h_m}{\sum_{i=m+1}^{M} p_i h_i + \sigma^2 B} \right) \ge r_m^{\min}. \tag{14}$$

Thus, $(\mathcal{P}2)$ can be formulated as follows (see Eq. (15)):

$$\max_{\mathbf{p}} \; B \log_2 \left(1 + \frac{\sum_{m=1}^{M} h_m p_m}{\sigma^2 B} \right) \tag{15a}$$

$$\text{s.t.} \quad h_m p_m \ge \left(2^{R_m^{\min}} - 1 \right) \left(\sum_{i=m+1}^{M} h_i p_i + \sigma^2 B \right), \tag{15b}$$

$$\forall m \in \{1, \dots, M\}, \tag{15c}$$

$$p_m \le p_m^{\max}, \quad \forall m \in \{1, \dots, M\}, \tag{15d}$$

$$L_{\text{control}} \le L_{\max}, \tag{15e}$$

$$\text{BER}_{\text{control}} \le \text{BER}_{\max}. \tag{15f}$$

The convexity of the problem in Eq. (15) allows for an effective resolution using CO techniques, such as the interior point method [17].

C. JOINT OPTIMIZATION: ALTERNATING ALGORITHM

Problem $(\mathcal{P})$ is a non-convex mixed-integer optimization problem because of the integer CA constraints, i.e., (7c) and (7d), and the non-concavity of its objective function. However, as we discussed in previous sections, fixing one optimization variable reduces problem $(\mathcal{P})$ to solvable sub-problems using CO methods, such as the gradient method and interior point method. This fact motivates the use of the alternating approach to solve problem $(\mathcal{P})$ sub-optimally.

D. CONVERGENCE AND COMPUTATIONAL COMPLEXITY ANALYSIS OF CO-BASED METHOD

This section delves into the convergence behavior and computational complexity of the alternating Co-based algorithm to ascertain its efficiency and reliability.

1) CONVERGENCE ANALYSIS

The algorithm guarantees optimal solutions for each sub-problem, $(\mathcal{P}1)$ and $(\mathcal{P}2)$, incrementally enhancing the sum-rate with each iteration. Considering the sum-rate's upper limit within the bounded feasible set of problem $(\mathcal{P})$, the algorithm's convergence is assured, marked by the cessation of indefinite sum-rate increase.

2) COMPUTATIONAL COMPLEXITY ANALYSIS

The purpose of Algorithm 2 is to provide an efficient solution to the JPACA problem by iteratively optimizing CA and PA. This algorithm ensures that both tasks are handled in a coordinated manner, improving overall system performance. The Alternating Algorithm for problem $(\mathcal{P})$, designated as Algorithm 2, incorporates two primary operations: (1) Channel Assignment (Algorithm 1) addressing $(\mathcal{P}1)$ with

Algorithm 2 Proposed Alternating Algorithm for Problem ($\mathcal{P}$) With Control Channel Consideration

Initialize $\mathbf{p}$
repeat
  Channel assignment ($\mathcal{P}1$): Perform the CA according to Algorithm 1.
  Check control channel constraints after CA: Ensure $L_{\text{control}} \leq L_{\max}$ and $\text{BER}_{\text{control}} \leq \text{BER}_{\max}$.
  Power allocation ($\mathcal{P}2$): Calculate the PA vector $\mathbf{p}$ based on the interior point algorithm.
  Check control channel constraints after PA: Ensure $L_{\text{control}} \leq L_{\max}$ and $\text{BER}_{\text{control}} \leq \text{BER}_{\max}$.
until convergence
Output: $\mathbf{X}^{\star}, \mathbf{P}^{\star}$

complexity $O(M^2N)$, and (2) PA via the interior point method for ($\mathcal{P}2$) with complexity $O(M^3)$.

- The CA algorithm manifests a complexity of $O(M^2N)$, dictated by the channel allocation process across M users and N subchannels.
- The PA, facilitated by the interior point method, exhibits $O(M^3)$ complexity, attributed to its polynomial-time operational characteristic in power distribution among M users.

Hence, the overall computational load of Algorithm 2 primarily hinges on the step with the highest complexity, leading to a more accurately depicted overall complexity of $O(M^3)$. This delineation considers the PA's computational intensity as the pivotal factor, especially under scenarios where user count (M) notably surpasses subchannel quantity (N), earmarking the PA phase as the computational crux.

V. ML-BASED METHOD

In addressing the challenges posed by the JPACA optimization problem in uplink NOMA networks, which are frequently difficult for convex-based optimization methods such as Algorithm 2 to solve in real-time, we propose an ML-based technique that leverages the capabilities of ML to learn complex relationships and provide efficient solutions. Our ML-based algorithm focuses on the following four key ML techniques: CNN, FNN, RF, and the Stacking Ensemble Method. To predict the optimal resource allocation in real-time, the algorithm learns from a training dataset generated using a CO-oriented algorithm, Algorithm 2, in an offline mode. This approach considerably reduces the computational burden, which makes this approach well-suited for large-scale systems. Operating with the channel gains $h_{m,n}$ as inputs, the ML model produces optimal solutions for both CA and PA, represented by $\mathbf{X}^{\star}$ and $\mathbf{p}^{\star}$, respectively. In the subsections below, we provide more detailed explanations of the proposed ML-based algorithm and its application to the JPACA problem.

A. TRAINING DATASET GENERATION

To train and evaluate our regression models for the JPACA problem in uplink NOMA networks, we generate a training dataset comprising 1 million instances of the problem ($\mathcal{P}$). Each instance, denoted as $h_{m,n}$, corresponds to a unique set of subchannel gains for users. The optimal CA and PA for each instance are computed using CO in an offline mode. Each BS is responsible for generating locally optimized data, which is then used to train the ML model. This offline data generation ensures that the real-time performance of the system is not impacted. In each independent run, Algorithm 2 is used to compute the optimal CA and PA for the given subchannel gains, which serve as the output labels. To ensure the robustness and generalization of our regression models, we perform data partitioning by dividing the generated samples into training, validation, and test datasets. The training dataset constitutes 70% of the total samples, providing a large and diverse set of instances for the models to learn from. The test dataset accounts for 10% of the data and is used to evaluate the models' performance on unseen instances. The remaining 20% of the data is reserved for the validation dataset, which plays a critical role in the model ensemble stage, such as during the stacking procedure. We employ a large training dataset along with a separate validation dataset to fine-tune the regression model's hyperparameters and to ensure strong generalization to unseen data. This rigorous process enhances the accuracy and reliability of the models in optimizing JPACA in uplink NOMA networks.

B. PRE-PROCESSING

In the context of our computational framework, the pre-processing phase plays a critical role in transforming raw data into a format that would seamlessly integrate with ML models. This essential phase encompasses a series of operations that collectively facilitate efficient data conversion. The primary objective is establishing the intricate relationship between the constant channel gains $\mathbf{H} = [h_{m,n}]$ as input parameters and the PA vector $\mathbf{p} = [p_m]$ and CA matrix $\mathbf{X} = [x_{m,n}]$ as output parameters. To effectively represent the CA matrix $\mathbf{X}$, we use a one-hot encoding approach. This format signifies that, for each user m, a solitary 1 is present in the column corresponding to the assigned subchannel, while all other elements are set to 0. For instance, if $\mathbf{X} = [[0, 1, 0, 0], [1, 0, 0, 0], [0, 0, 1, 0]]$, user 1 is allocated to subchannel 2, user 2 to subchannel 1, and user 3 to subchannel 3. To adapt this CA data for a regression problem, we undertake the conversion of the one-hot encoded $\mathbf{X}$ into a vector form denoted as $\bar{\mathbf{x}} = [\bar{x}_m]$. In this vector, each $\bar{x}_m$ indicates the index of the non-zero element in the m-th row of $\mathbf{X}$. In the aforementioned example, the transformation results in $\bar{\mathbf{x}} = [2, 1, 3]$. This vector is subsequently used as the target output for our ML models. Through the application of this pre-processing scheme, we successfully render the raw data interpretable for ML models, while concurrently elevating their learning and predictive capabilities. This strategic approach ensures that the inputs to our models are imbued with theoretical robustness, practical implementability, and an environment conducive to achieving optimal performance in the realm of uplink NOMA networks.

C. POST-PROCESSING

The efficacy and reliability of our proposed solution largely depend on the accuracy achieved during the post-processing phase. This crucial stage is dedicated to the vital task of converting the continuous-valued estimates generated by our ML models into discrete CAs. To ensure the validity and practicality of this transformation, we have rigorously implemented comprehensive verification and validation processes, meticulously scrutinizing every aspect of the post-processing procedure. The ML model's output for a specific user is denoted by y_{pred}, representing the anticipated CA as a continuous variable. With M users and N subchannels, the model's output is presented as a matrix $O = [o_{m,n}]$, where $m \in \mathcal{M}$ and $n \in \mathcal{N}$. Each element $o_{m,n}$ signifies the predicted allocation of user m to subchannel n. For instance, let us consider a scenario where the model generates the output $Y_{\text{pred}} = [1.6, 0.9, 2.8]$. Since these values are continuous, they must be discretized into integer indices representing the assigned subchannels. Considering the inherent discreteness of user-to-subchannel assignments in our problem, the continuous predictions undergo the following multi-step process to acquire discrete indices:

1) *Rounding:* The initial step involves rounding each $o_{m,n}$ to the nearest integer, resulting in $o'_{m,n}$. In the aforementioned example, this operation yields $Y'_{\text{pred}} = [2, 1, 3]$.
2) *Indexing:* Next, we obtain a matrix of integers $O' = [o'_{m,n}]$. However, these values are not yet indices. To represent CAs for each user, we use the max function to find the maximum value in each row of O', effectively assigning each user to a specific subchannel. The resulting index vector is denoted by $I = [m_k]$, where m_k indicates the index of the subchannel assigned to user k. Mathematically, this operation is represented as $m_k = \max_n(o'_{k,n})$, $\forall k \in [1, M]$. Subsequently, these indices are translated into actual assignments by creating a one-hot encoded matrix, resulting in $X'_{\text{pred}} = [[0, 1, 0, 0], [1, 0, 0, 0], [0, 0, 1, 0]]$.

Following this post-processing procedure, we successfully convert the continuous-valued predictions from our ML models into feasible, discrete CA.

D. REGRESSION MODEL

In addressing the JPACA problem in uplink NOMA networks, we utilize ensemble learning techniques and regression models to model the continuous relationships between channel gains as inputs and optimal PA and CA as outputs.

1) CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNNs capture spatial relationships in the received signal matrix and user indices. Our CNN model consists of four convolutional layers for feature extraction, followed by a MaxPooling2D layer for downsampling, a Flatten layer for vector transformation, and two Dense layers for final predictions. Batch normalization and activation functions (ReLU for hidden layers and linear for the output layer) enhance performance. Through training, CNN minimizes the mean squared error (MSE) loss. CNN excels at capturing spatial relationships within the signal matrix and user indices, crucial for regression analysis. However, it is computationally intensive and requires large datasets for optimal training. To address this, we incorporate FNN and RF into our ensemble.

2) FEED-FORWARD NEURAL NETWORKS (FNN)

FNNs, or multilayer perceptrons, capture complex nonlinear relationships. Our FNN model has two Dense layers, activation functions (ReLU for hidden layers and linear for the output layer), and batch normalization. It is trained using the MSE loss function and the Adam optimizer. FNNs are versatile and adaptable across tasks, learning complex nonlinear relationships. They struggle with spatial/temporal dependencies without complex adjustments, which is mitigated by the spatial modeling strength of CNNs and the robustness of RFs.

3) RANDOM FOREST (RF)

RF combines multiple decision trees for robust regression. Each tree independently makes predictions, aggregated by RF to determine optimal PA and CA values. The number of decision trees, or estimators, can be adjusted for optimal performance. RF is evaluated using MSE and accuracy. RF is chosen for its resistance to overfitting, handling outliers and non-linear data effectively, and ensuring robustness in dynamic NOMA networks. RF's reduced interpretability and longer training times with extensive datasets are balanced by the efficiency of CNNs and the versatility of FNNs.

4) STACKING ENSEMBLE METHOD

Utilizing the specialized strengths of CNN, FNN, and RF, our approach incorporates the stacking ensemble method to enhance the efficacy of regression models for the JPACA issue within uplink NOMA networks. By merging the predictions from each distinct model, we create a unified, powerful ensemble forecast that leverages CNN's skill in spatial feature extraction, FNN's capability in understanding complex nonlinear relationships, and RF's robustness in decision boundary determination. We recognize the slight increase in computational latency due to the ensemble approach as a deliberate trade-off, justified by the marked improvement in predictive performance and the method's adaptability to varying network conditions.

The principle behind the stacking ensemble is to use a meta-model to learn how to best combine the predictions of

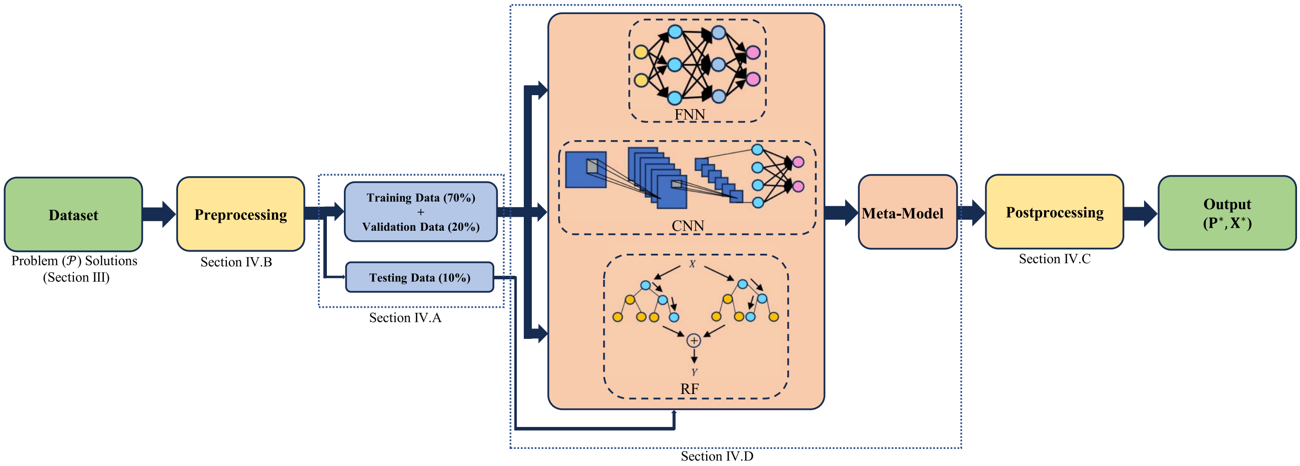

FIGURE 2. An overview of stacking ensemble technique in our ML process.

the base models. This involves training multiple base models independently and then using their predictions as inputs for a higher-level learner, the meta-model, which makes the final prediction.

Figure 2 illustrates the design of our stacking ensemble method. The process begins with the dataset, which is preprocessed and divided into training, validation, and testing sets. The training and validation data are used to train the base models: CNN, FNN, and RF. Each base model captures different aspects of the data:

- *CNN:* Excels at capturing spatial relationships in the received signal matrix and user indices.
- *FNN:* Learns complex non-linear relationships.
- *RF:* Handles decision boundary determination and robustness to outliers.

The predictions from these base models are concatenated to form stacked inputs, which are then fed into a meta-model. In our study, the meta-model is an RF regressor trained to minimize the MSE between the predicted values and the actual target labels. This ensures that the ensemble leverages the complementary strengths of each base model, improving overall prediction accuracy and robustness.

Mathematically, let us denote the predictions of the CNN, FNN, and RF models as CNN_{pred}, FNN_{pred}, and RF_{pred}, respectively. The stacked inputs, denoted as $Stack_{\text{pred}}$, can be represented as:

$$Stack_{\text{pred}} = \left[CNN_{\text{pred}}, FNN_{\text{pred}}, RF_{\text{pred}}\right] \tag{16}$$

The meta-model, denoted as M_s, takes the $Stack_{input}$ as the input data and aims to learn the optimal parameters that minimize the MSE between the predicted values and the actual target labels:

$$MSE = \frac{1}{N_s}\sum_{i=1}^{N_s}\left(M_s(Stack_{\text{input}}) - y_{\text{target}}\right)^2 \tag{17}$$

where N_s is the number of samples in the dataset.

Postprocessing is applied to the meta-model's output to generate the optimal power and channel allocations ($\mathbf{X}^\star$, $\mathbf{P}^\star$). This method not only enhances the predictive performance but also ensures adaptability to varying network conditions. Detailed discussions on each step of this process can be found in Sections IV-A–IV-D.

E. COMPUTATIONAL COMPLEXITY ANALYSIS OF ML-BASED METHOD

Importantly, the inherent computational complexity of both base learners and top models, crucial to ensemble methodologies like stacking, is capped at $\mathcal{O}(N^2)$ [18]. Compared to the CO-based method, which exhibits a complexity of $\mathcal{O}(M^3N)$, the ML-driven strategy exhibits a significant computational efficiency. Moreover, the innate scalability of the ML-based method allows for extensive training on voluminous datasets, ensuring efficacious use across varied operational terrains without the need for perpetual recalibration.

By incorporating the stacking ensemble method into our research, we enhance the regression models' predictive capabilities in optimizing JPACA in uplink NOMA networks. This method not only improves prediction performance but also ensures adaptability to varying network conditions. The combination of CNN, FNN, and RF models through the stacking ensemble approach offers a robust and accurate solution to address the complexities of the problem. This methodology holds promise in terms of improving the performance and efficiency of wireless communication systems in real-world scenarios, thereby contributing to the advancement of uplink NOMA networks.

VI. SIMULATION RESULTS AND COMPUTATIONAL COMPLEXITY

In this section, we present the results derived from the evaluation of the proposed convex-based and ML-based algorithms, in numerical simulations. The system parameters for the BS and users are established as shown in Table 2.

TABLE 2. System parameters for users and BS.

Symbol	Description	Value
M	Number of users	16
N	Number of subchannels	16
N_0	Noise power spectral density	-174 dBm/Hz
σ^2	Gaussian noise power density	2.5×10^{-15} Watt
f	Carrier frequency	5 GHz
N_f	Noise figure	58 dB
$BW_n, n \in \mathcal{N}$	Bandwidth of n-th subchannel	3 MHz

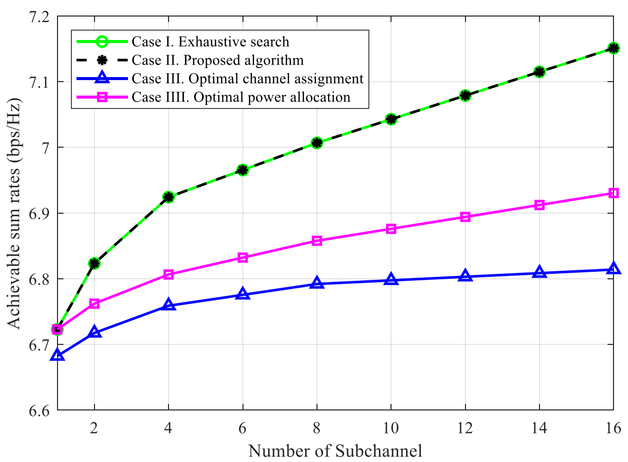

FIGURE 3. Total achievable rate as a function of the number of subchannels, assuming *M* users and a subchannel capacity of *A* = 2.

The channel gains for each effective path, represented as h_{mn}, are modeled as ($h_{mn} = |h^{pl}_{mn} h^{ls}_{m} h^{ss}_{mn}|, m, n \in \mathcal{M}, \mathcal{N}$), where $h^{pl}_{mn} = (\lambda/4\pi d_m)^2$ signifies the open space path loss coefficient, while $h^{ss}_{mn}, h^{ls}_{m} \sim \mathcal{CN}(0, 1)$ denote the large-scale shading coefficient and the Rayleigh fading coefficient, respectively [19], [20].

A. EVALUATION OF CONVEX-BASED METHODS

We present the results of our convex-based methods in terms of achievable sum rates with respect to both the number of subchannels and the number of users. The performance of the proposed algorithm is compared against three other cases: exhaustive search, optimal CA, and optimal PA.

1) ACHIEVABLE SUM RATES VS. NUMBER OF SUBCHANNEL

The variation of achievable sum rates with respect to the number of subchannels for the different methods is illustrated in Figure 3. The figure shows that the proposed algorithm (Case II) demonstrates a higher sum rate, particularly as the number of subchannels increases. This indicates the effectiveness of the proposed method in harnessing the potential of multiple subchannels. The Exhaustive Search (Case I) and the Proposed Algorithm (Case II) converge to similar values with an increase in the number of subchannels, suggesting that the efficiency of the proposed algorithm approaches the exhaustive search in high subchannel scenarios. By contrast, the Optimal CA (Case III) and Optimal PA (Case IV) show sub-linear growth with the number of subchannels. This indicates that, while they provide benefits in terms of power and channel utilization, they might not be as efficient in scenarios with a large number of subchannels.

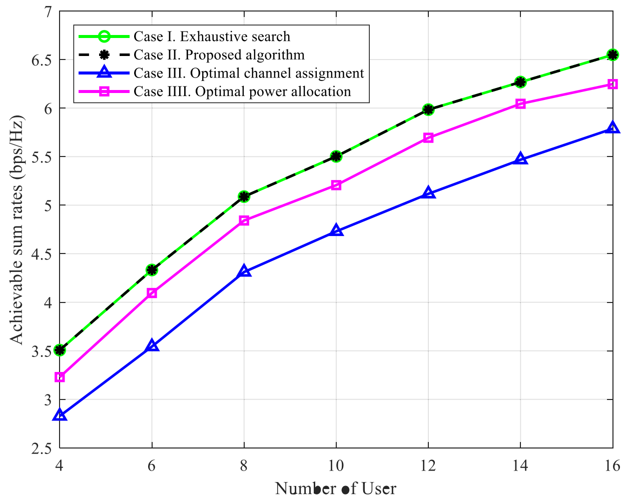

FIGURE 4. Total achievable rate as a function of the number of users, assuming *N* subchannel and a user capacity of (6d).

2) ACHIEVABLE SUM RATES VS. NUMBER OF USERS

Figure 4 showcases the achievable sum rates against the number of users. With an increase in the number of users, the proposed algorithm consistently outperforms the other cases. This finding underscores the algorithm's capability to efficiently allocate resources even in dense network scenarios. While the Exhaustive Search (Case I) offers competitive performance, its computational complexity becomes a limiting factor in practical scenarios. Conversely, both the Optimal CA (Case III) and Optimal PA (Case IV) exhibit a steady increase in the achievable sum rate; however, they lag behind the proposed algorithm. Of note, the gap between the proposed algorithm and the other methods widens with an increase in the number of users. This further underscores the scalability and robustness of the proposed algorithm in dense deployments.

3) ANALYSIS SUMMARY

A comparison of Optimal CA (Case III) and Optimal PA (Case IV) suggests that each method's singular focus results in inherent inefficiencies. Case III, which prioritizes spectral efficiency, frequently overlooks optimal power distribution, leading to potential power wastage. Conversely, Case IV, while adept at PA, can sometimes allocate power to suboptimal channels, which undermines its effectiveness. Albeit beneficial in their specific domains, these isolated approaches fall short of maximizing the sum rate, particularly in dense network scenarios. Yet efficient communication systems must concurrently consider

TABLE 3. Analysis of computation latency for 10,000 samples employing co-based and ML-based resource allocation methods.

Methods	Algorithm 2		Stacking		FNN		RF		CNN	
	Acc (%)	Time (ms)	Acc (%)	Time (ms)	Acc (%)	Time (ms)	Acc (%)	Time (ms)	Acc (%)	Time (ms)
$M=2, N=2$	100	627149	99.61	323	99.82	232	99.32	257	98.40	290
$M=4, N=2$	100	1110800	97.74	449	96.50	266	96.30	284	97	364
$M=8, N=4$	100	1571400	94.78	1460	94.12	301	94.51	337	92	489

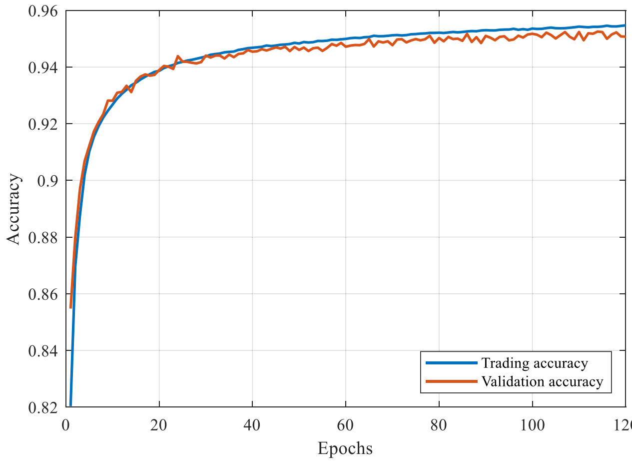

FIGURE 5. Stacking ensemble's precision beyond power predictions.

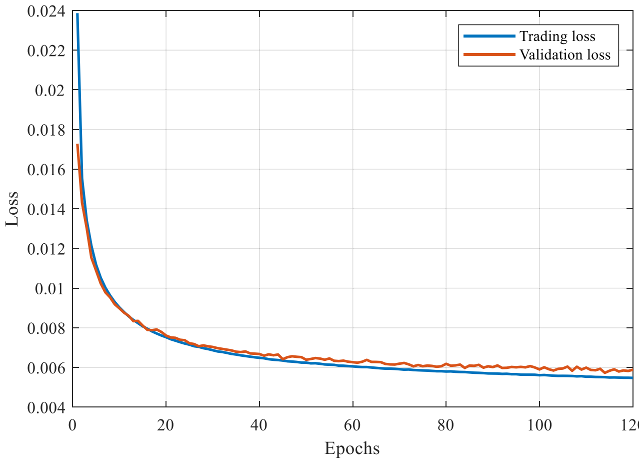

FIGURE 6. MSE for resource allocation using the stacking ensemble meta-model.

both channel quality and PA. An adaptive solution that dynamically balances these factors, such as the proposed one, offers superior performance in complex communication environments.

B. EVALUATION OF ML MODEL PERFORMANCE

In this section, we evaluate the efficacy of diverse ML methodologies in optimizing the JPACA process within wireless communication systems. To this end, we undertake a comprehensive comparison of the outcomes against those obtained from a proposed algorithm. Performance evaluation relies on the employment of MSE and computational time efficiency as essential performance metrics.

1) PERFORMANCE EVALUATION

The proposed algorithm consistently demonstrates lower MSE values across diverse user and subchannel modes, which means superior precision in power and channel allocation. This enhanced accuracy is particularly pronounced in the context of NOMA, wherein the algorithm adeptly manages user interference within the same cell, resulting in an elevated system performance. Figure 5 provides a visual representation of performance across different user and subchannel modes under the proposed algorithm. The algorithm sustains robust performance across varying scenarios, effectively overseeing power and channel allocation, even in demanding conditions. Upon adopting the stacking mode, the composite model showcases a significantly minimized mean square error, (see Figure 6). This outcome underscores the amalgamation of algorithmic components within ML networks, effectively discerning complex patterns and relationships. Consequently, more advanced resource optimization and improved data collection rates are achieved.

2) COMPUTATIONAL EFFICIENCY

Table 3 showcases the comparative computation latencies between the conventional Algorithm 2 and various ML methodologies. Notably, while Algorithm 2 consistently achieves a perfect accuracy score across configurations, it does so at the expense of substantial computation time. For instance, for a configuration of $M = 2$, $N = 2$, the ML-based model, specifically the Stacking method, yields an accuracy of 99.61% but takes only 323 *ms*, in stark contrast to the 627,149 *ms* required by Algorithm 2. This outcome demonstrates the computational prowess of ML-based methods in handling the resource allocation problem without significant losses in accuracy.

3) COMPARATIVE PERFORMANCE ANALYSIS

The performance of the stacking ensemble model is evaluated using well-established metrics including MSE, Root Mean Squared Error (RMSE), and R-squared. These metrics specify the model's predictive error, accuracy, and data fit. Specifically, lower MSE and RMSE values underscore higher accuracy, whereas an elevated R-squared value reflects a commendable fit to the target labels. Table 4 provides a detailed comparison between the stacking ensemble and other ML models. As the table shows, the stacking ensemble method consistently outshines the best individual ML

TABLE 4. Comparative performance analysis of stacking ensemble and ML models.

Model	MSE	RMSE	R-squared
CNN	0.0052	0.072	0.92
FNN	0.0048	0.069	0.93
RF	0.0045	0.067	0.94
Stacking Ensemble	0.0025	0.05	0.96

model across all metrics. For instance, the MSE for the Stacking-Model is 0.0025, which is substantially lower than the corresponding value of the top-performing standalone ML model. Similarly, its RMSE and R-squared values, registered at 0.05 and 0.96, respectively, further accentuate the ensemble's exceptional performance. The results of this comparative analysis underline the superior precision and robustness of the stacking ensemble model in the realm of ML methodologies.

VII. POTENTIAL FUTURE APPLICATIONS

The advancements made in JPACA in uplink NOMA networks through CO and ML techniques hold significant promise for a variety of future applications. These methods can be directly applied to enhance the performance and efficiency of 5G and beyond wireless networks, which require sophisticated resource allocation to support a vast number of devices and diverse use cases. Additionally, the Internet of Things (IoT) can benefit greatly from these techniques, as they enable scalable, reliable, and energy-efficient communication among countless connected devices with varying QoS needs. In the realm of Vehicle-to-Everything (V2X) communications, optimized resource allocation is crucial for enabling low-latency, high-data-rate interactions that improve traffic management and safety. Similarly, smart grid communications can leverage these advancements to enhance real-time monitoring, control, and management of energy distribution. Furthermore, the high data rate and low latency requirements of Augmented and Virtual Reality (AR/VR) applications can be better met with these techniques, providing more immersive user experiences. Public safety networks, which demand robust and efficient communication in emergency situations, can also be significantly improved. Lastly, satellite and aerial communication networks can utilize these methods to ensure better coverage and reliability, particularly in remote or underserved regions. By addressing the complex challenges of resource allocation in NOMA networks, this work contributes to the development of more efficient, reliable, and scalable communication systems across a wide range of advanced applications.

VIII. CONCLUSION

In this study, we conducted a comprehensive evaluation of power and channel allocation methodologies for wireless communication systems. The proposed convex-based algorithm and ML techniques were scrutinized for their effectiveness in optimizing JPACA. The results highlight the potential of these methodologies to enhance the efficiency and reliability of wireless communication systems. More specifically, the proposed algorithm exhibited remarkable computational efficiency, demonstrating its applicability in real-time processing scenarios. Through careful optimization of power and channel allocation, the algorithm consistently achieved lower MSE values, which indicates its accuracy in power distribution. Performance gains, particularly evident in scenarios involving NOMA, illustrate its effectiveness in managing user interference and improving the overall system performance. Furthermore, the integration of ML methodologies showcased their capacity to discern intricate patterns within data, thereby enabling precise predictions for optimal CA and PA. The stacking ensemble model, in particular, demonstrated improved prediction accuracy, as evidenced by its lower MSE and RMSE values. The higher R-squared value for the stacking ensemble model highlights its better fit to the target labels, showcasing its potential in wireless communication systems. Collectively, the results of this study emphasize the significance of harmonizing JPACA methodologies, which can lead to elevated achievable aggregation rates. These methodologies are poised to revolutionize the efficiency, reliability, and performance of wireless communication systems, particularly in scenarios employing NOMA techniques.

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