Deep Learning-Based Joint User Clustering and Pairing for UAV-Assisted NOMA

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Abstract—**Unmanned aerial vehicles (UAVs) are reshaping the field of wireless communication promising to improve coverage, connectivity and service quality in future wireless communication networks. An UAV-assisted system can improve spectral efficiency by serving multiple users simultaneously within the same time/frequency resources when integrated with a non-orthogonal multiple access (NOMA) system. However, the performance of UAV-assisted NOMA networks is highly dependent on the effective user clustering and pairing strategies, which typically incur high computational complexity and limited adaptability to dynamic wireless environments. In this paper, we have considered a deep learning based framework for user clustering and pairing in a UAV-assisted non-orthogonal multiple access (UAV-ANOMA) system. The process begins with clustering users based on their channel features and network locations using the K-means algorithm, which facilitates pairing and reduces the search space. Then, the appropriate user pairs in each cluster are obtained using an MLP based classification model with the channel gain and distance related information. The proposed framework learns pairing patterns directly from data unlike traditional iterative optimization approaches, leading to faster decisions and improved scalability. This results in an efficient user pairing with much reduced computational complexity and good network performance. The proposed framework is evaluated by extensive simulations and the performance is compared with conventional NOMA and UAV-NOMA schemes. The results indicates that this method achieves higher system throughput, better user fairness and better scalability, while keeping the computational complexity low. These results demonstrate the potentials of deep learning techniques for intelligent resource management in future aerial communication networks.**

Index Terms— **UAV, NOMA, User Clustering, User Pairing, Deep Learning, MLP, Throughput Optimization**

I. Introduction

Modern wireless networks are experiencing a substantial increase in data traffic and the demand for high data rates have motivated the development of advanced multiple access techniques and more flexible network architectures. Recently, unmanned aerial vehicles have gained significant interest as potential aerial base stations. Thus, UAV-enabled communication can be efficient in supporting the coverage and is especially useful in emergency situations and highly populated areas [1,2]. The flexible deployment capability of UAVs, together with their ability to establish favorable air-to-ground communication links, makes them attractive for enhancing wireless network coverage and service quality [3].

In parallel, non-orthogonal multiple access has gained considerable attention as an efficient multiple access technique that enables improved utilization of available spectrum resources in future communication networks [4,5]. Power domain multiplexing enables several users to utilize the same time and frequency resources simultaneously, resulting in increased throughput compared to conventional orthogonal multiple access methods. The overall effectiveness of a NOMA network is heavily dependent on how users are matched and how transmission power is allocated among them [6]. In practical implementations, users experiencing significantly different channel conditions are typically assigned to the same resource block. Such a pairing strategy facilitates the operation of successive interference cancellation (SIC), allowing the receiver with the stronger channel gain to decode and remove interference before recovering its own information signal [7]. Consequently, efficient user pairing plays an important role in improving spectrum utilization and communication reliability.

The combination of UAV-enabled communications and NOMA has attracted considerable research interest as an effective approach for improving network coverage, increasing system capacity, and supporting a growing number of wireless users [8]. UAV-assisted

NOMA systems can dynamically adjust their positions to improve channel conditions and provide better service to ground users [9]. Several studies have investigated joint optimization problems involving UAV deployment, power allocation and bandwidth allocation [10,11]. However, these approaches often rely on complex optimization techniques such as successive convex approximation and path-following algorithms, which incur high computational complexity. Despite the advantages of UAV-ANOMA systems, several challenges remain in achieving efficient resource allocation. In particular user pairing and clustering plays a critical role in determining system performance. Conventional approaches rely on exhaustive search, matching algorithms or heuristic-based methods [12]. These methods can achieve near optimal performance, however the computational complexity increases with the large number of users, making them impractical for real-time applications.

To address scalability issues, machine learning techniques have recently been introduced for wireless communication optimization [13]. In particular, a deep neural networks (DNNs) and graph neural networks (GNNs) have demonstrated strong capabilities in addressing user clustering, resource allocation, and interference management, demonstrating outstanding performance in these tasks. These learning-based methods are capable of capturing intricate interactions among network parameters while producing decisions with minimal processing delay. Such characteristics make these methods attractive for wireless environments where channel conditions and user requirements vary over time [14]. Motivated by these advantages, the present work introduces a learning-driven approach for jointly performing user clustering and pairing in UAV-assisted ANOMA networks. In this work, we propose an efficient and scalable user grouping scheme by combining K-means clustering and multi layer perceptron. A learning based approach instead of conventional optimization schemes can greatly reduce the computational complexity while maintaining the high throughput.

A. Contributions

To improve the efficiency of user grouping in UAV-ANOMA systems, a deep learning framework is developed that performs both clustering and pairing based on network conditions and user characteristics. The proposed framework combines the machine learning techniques with UAV enabled communication to enhance the efficiency of user grouping by reducing computational complexity. The key contributions of this research are outlined below:

- A wireless network architecture based on UAV-assisted NOMA is formulated, where communication support is provided to geographically dispersed users through an aerial relay platform. The adopted model captures the characteristics of air-to-ground transmission links and user-dependent channel variations.
- We propose a deep learning based user clustering and pairing scheme, which can cluster the users intelligently according to the channel conditions, thus improving the system throughput.
- The framework incorporates an adaptive power allocation scheme, which dynamically assigns transmission power to weak and strong users to improve spectral efficiency.
- Simulation-based analysis is carried out to assess the effectiveness of the proposed method. Numerical findings indicate noticeable gains in both throughput and user fairness when compared with conventional NOMA and UAV-ANOMA methods.
- The proposed method significantly reduces computational complexity of conventional optimization based approaches, and makes it applicable for large scale networks.

II. UAV-assisted Non-Orthogonal Multiple Access System Model

A detailed description of the proposed UAV-assisted communication framework is presented in this section. The network architecture, channel model, and transmission scheme are explained in detail.

A. System Model

The proposed UAV-assisted NOMA communication system is shown in Figure 1. A ground base station (BS) communicates with a UAV via a wireless backhaul link. Since obstacles obstruct the propagation path between the terrestrial station and users located on the ground, direct signal transmission cannot be maintained. To overcome this limitation, the aerial platform provides communication services to multiple users distributed across the coverage area. The UAV is deployed at a fixed altitude H with horizontal coordinates (x_u, y_u) while the location of the i-th user is represented by (x_i, y_i). Since communication occurs through an aerial platform, the propagation path depends on both the elevation of the UAV and the spatial distribution of users on the ground. The UAV performs power domain non-orthogonal multiple access transmission by generating superposed signals for multiple users over the same spectrum resources. This UAV-assisted NOMA framework improves coverage, spectral efficiency and communication reliability in dense wireless environments. The distance that separates the UAV from user i can be defined as

$$d_i^{\text{UAV}} = \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + H^2} \tag{1}$$

For the conventional NOMA system with a ground BS, the distance is expressed as

$$d_i^{\text{BS}} = \sqrt{x_i^2 + y_i^2} \tag{2}$$

Users are divided into cell-center (strong) and cell-edge (weak) users based on the channel conditions.

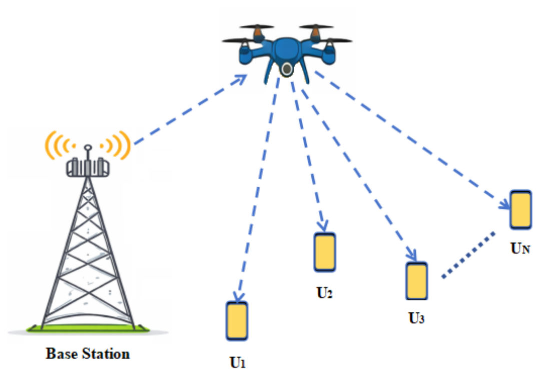

Fig. 1. Network deployment of the UAV-assisted multi-user communication system

B. Channel Model

1) UAV-Assisted Channel: Due to its elevated position, primarily establishes line-of-sight communication links with users on the ground. Consequently, the air-to-ground channel experiences lower path loss compared to conventional terrestrial communications. The channel gain, which measures the strength of the signal between the UAV and user i.

$$h_i^{\text{UAV}} = \frac{\beta_0}{(d_i^{\text{UAV}})^{\alpha_{\text{UAV}}}} \tag{3}$$

where β_0 is the channel gain measured at a certain reference distance and d_i^{UAV} is the distance between the UAV and user i. The parameter α_{UAV} is the path loss exponent for signal attenuation in UAV to user channel.

2) Ground BS Channel: For performance comparison, a conventional NOMA system with a ground base station is also considered. Due to non-line-of-sight (NLoS) propagation and environmental obstructions, the terrestrial channel experiences higher attenuation. The corresponding channel gain is expressed as

$$h_i^{\text{BS}} = \frac{\beta_0}{(d_i^{\text{BS}})^{\alpha_{\text{BS}}}} \tag{4}$$

where d_i^{BS} denotes the distance between the BS and user i, and α_{BS} is the terrestrial path-loss exponent with

$$\alpha_{\text{BS}} > \alpha_{\text{UAV}}. \tag{5}$$

3) NOMA Transmission Model: In power-domain NOMA, several users share identical radio resources through signal superposition at the transmitter. The composite signal generated for transmission can be written as

$$x = \sum_{i=1}^{N} \sqrt{P_i}\, s_i \tag{6}$$

The quantity P_i specifies the portion of transmit power assigned to user i, whereas s_i denotes the corresponding normalized message symbol satisfying $\mathbb{E}[|s_i|^2] = 1$.

The received waveform associated with user i can be written as

$$y_i = h_i x + n_i \tag{7}$$

In the above relation, h_i represents the channel coefficient corresponding to user i. The term n_i models random receiver noise and follows a complex Gaussian distribution with zero mean and variance σ^2, i.e., $n_i \sim \mathcal{CN}(0, \sigma^2)$. Consider a NOMA pair consisting of a weak user w and a strong user s. The weak user decodes its signal treating the strong user's signal as interference, while the strong user first decodes and removes the weak user's signal using SIC before decoding its own signal. The signal-to-interference-plus-noise ratio (SINR) of the weak user is

$$\gamma_w = \frac{P_w |h_w|^2}{P_s |h_w|^2 + \sigma^2}. \tag{8}$$

The corresponding achievable rate is

$$R_w = \log_2 (1 + \gamma_w). \tag{9}$$

After SIC, the SINR of the strong user becomes

$$\gamma_s = \frac{P_s |h_s|^2}{\sigma^2}, \tag{10}$$

and its achievable rate is

$$R_s = \log_2 (1 + \gamma_s). \tag{11}$$

The total system throughput is defined as

$$R_{\text{total}} = \sum_{i=1}^{N} R_i. \tag{12}$$

To guarantee successful SIC and fairness among users, a larger portion of the transmit power is allocated to users with weaker channel conditions. For a two-user NOMA pair, the power allocation is given by

$$P_w = \beta P_{\max}, \qquad P_s = (1-\beta) P_{\max} \tag{13}$$

where $\beta \in (0.5, 1)$ and $P_{\max}$ denotes the maximum transmit power. The objective of the system is to maximize the overall throughput,

$$\max_{\{P_i\}} \sum_{i=1}^{N} R_i \tag{14}$$

subject to

$$\sum_{i=1}^{N} P_i \leq P_{\max} \tag{15}$$

and

$$\sum_{j=1}^{N} a_{ij} \leq 1, \qquad \forall i, \tag{16}$$

where $a_{ij} \in \{0,1\}$ indicates whether user i is assigned to pair j. The above optimization problem is non-convex because of the coupled relationship between user pairing and power allocation. Therefore, a learning-based approach is adopted to obtain efficient pairing decisions with reduced computational complexity.

III. Proposed Method

This section presents the proposed learning-based user pairing framework for UAV-assisted NOMA systems. The objective is to identify suitable user pairs with reduced computational complexity while maintaining high throughput performance. Unlike conventional optimization-based pairing approaches that require exhaustive search among multiple user combinations, the proposed framework utilizes a Multi-Layer Perceptron (MLP) to learn pairing decisions directly from user channel and location information.

The adopted approach involves three key processes: constructing input data representations, training the MLP classifier, and selecting appropriate user combinations. Once trained, the model can rapidly determine appropriate user pairs without repeatedly solving computationally intensive optimization problems. The complete algorithm process is shown in Algorithm 1.

A. Feature Extraction

The input feature quality is important for the performance of the learning model. Since user pairing in UAV-assisted NOMA is influenced by both channel conditions and user locations, a feature vector is constructed for each candidate user pair (i, j) as

$$\mathbf{z}_{ij} = [h_i,\ h_j,\ d_i,\ d_j] \tag{17}$$

where h_i and h_j denote the channel gains of users i and j, respectively, while d_i and d_j represent the corresponding distances between the UAV and the users. These features jointly capture the channel quality and spatial characteristics of the users, enabling the learning model to distinguish favorable and unfavorable pairing combinations.

B. MLP-Based Pairing Network

The extracted feature vector is provided as input to a MLP classifier consisting of an input layer, hidden layers, and an output layer. The input feature vector is processed through the first layer of the neural network to generate an intermediate representation, which can be written as

$$\mathbf{h}^{(1)} = \sigma\left(W^{(1)}\mathbf{z}_{ij} + b^{(1)}\right) \tag{18}$$

The parameters $W^{(1)}$ and $b^{(1)}$ are optimized during network training. The activation operation $\sigma(\cdot)$ enhances the representation capability of the model by enabling nonlinear feature extraction. The second hidden layer is given by

$$\mathbf{h}^{(2)} = \sigma\left(W^{(2)}\mathbf{h}^{(1)} + b^{(2)}\right) \tag{19}$$

The output layer generates a pairing probability through a sigmoid activation function:

$$\hat{p}_{ij} = \mathrm{sigmoid}\left(W^{(3)}\mathbf{h}^{(2)} + b^{(3)}\right) \tag{20}$$

where $\hat{p}_{ij} \in [0,1]$ denotes the probability that users i and j form a suitable NOMA pair.

C. Model Training

The MLP is trained using supervised learning. Training samples are generated from user channel characteristics and corresponding pairing labels obtained from conventional pairing strategies. Model training is carried out by minimizing the binary cross-entropy objective, which measures the discrepancy between the actual pairing decisions and the outputs generated by the MLP:

$$\mathcal{L} = -\frac{1}{M}\sum_{k=1}^{M}\left[y_k \log(\hat{y}_k) + (1-y_k)\log(1-\hat{y}_k)\right] \tag{21}$$

In the above expression, M specifies the size of the training samples. The term y_k corresponds to the reference pairing decision, while $\hat{y}_k$ is the confidence score produced by the classifier for the same sample.

D. Pairing Decision

After training, the MLP predicts the suitability of each candidate pair. The final pairing decision is determined using

$$p_{ij} = \begin{cases} 1, & \hat{p}_{ij} \geq \tau \\ 0, & \hat{p}_{ij} < \tau \end{cases} \tag{22}$$

where τ denotes a predefined classification threshold. Pairs satisfying the threshold condition are selected for NOMA transmission, while the remaining pairs are discarded.

Algorithm 1 Proposed MLP-Based User Pairing for UAV-NOMA

Require: User locations (x_i, y_i), UAV position (x_u, y_u, H), trained MLP model, threshold τ
Ensure: Selected NOMA user pairs and system throughput

Generate N user locations within the coverage area
for $i = 1$ to N **do**
  Compute UAV-user distance d_i
  Compute channel gain h_i
end for
Generate all candidate user pairs (i, j)
for each candidate pair (i, j) **do**
  Construct feature vector

$$\mathbf{z}_{ij} = [h_i,\ h_j,\ d_i,\ d_j]$$

  Input $\mathbf{z}_{ij}$ into the trained MLP
  Obtain pairing probability $\hat{p}_{ij}$
  if $\hat{p}_{ij} \geq \tau$ **then**
    Select pair (i, j)
  else
    Discard pair (i, j)
  end if
end for
Form final NOMA user pairs
Perform power allocation for each selected pair
Calculate total system throughput
return Selected user pairs and R_{total}

IV. Results and Discussion

This section analyzes the proposed deep learning-based UAV-ANOMA framework under different network conditions. The results are compared with conventional NOMA and UAV-ANOMA schemes without intelligent pairing. The evaluation focuses on system throughput, scalability, fairness, and user experience.

The simulation parameters used for performance evaluation are summarized in Table I.

TABLE I
Simulation Parameters

Parameter	Value
Number of users (N)	100
Cell radius (R)	500 m
UAV altitude (H)	120 m
SNR range	0 to 30 dB
SNR step size	2 dB
Number of iterations	300
UAV path loss exponent (α_{UAV})	2.2
BS path loss exponent (α_{BS})	3.2
Noise variance (σ^2)	1

A downlink wireless network is modeled within a circular service region having a radius of $R = 500$ m where N users are uniformly distributed across the coverage area. An unmanned aerial vehicle is deployed at an altitude of $H = 120$ m to provide communication services to ground users. To model channel propagation, the path-loss exponents are set to $\alpha_{\text{UAV}} = 2.2$ for the UAV-assisted link and $\alpha_{\text{BS}} = 3.5$ for the terrestrial BS link. In addition, additive white Gaussian noise (AWGN) with variance σ^2 is assumed at the receiver, and the transmit power is normalized throughout the simulations.

A. Performance Analysis

Figure 2 illustrates the throughput performance of Conventional NOMA, UAV-NOMA, and the proposed MLP-based UAV-NOMA scheme for different SNR values from 0 dB to 30 dB. As expected, the throughput of all schemes increases with increasing SNR due to the improvement in signal quality and reduced impact of noise. The conventional NOMA system exhibits the lowest throughput performance across the entire SNR range. This behavior is mainly attributed to the severe path loss and blockage effects experienced by the ground base station, resulting in weaker channel conditions for users located far from the transmitter. Consequently, the achievable data rates remain relatively limited even at high SNR values.

In contrast, the UAV-ANOMA scheme significantly improves system throughput by exploiting the favorable air-to-ground communication links provided by the UAV. The elevated position of the UAV increases the probability of line-of-sight communication, reduces propagation loss, and enhances channel quality for the served users. As a result, UAV-ANOMA consistently outperforms the conventional NOMA system throughout the considered SNR range. The proposed MLP-based UAV-ANOMA approach achieves the highest throughput performance among all compared schemes. By intelligently selecting user pairs based on channel and distance characteristics, the proposed framework effectively exploits channel disparities between users and improves resource utilization. The learning-based pairing strategy enables more efficient NOMA transmission, resulting in additional throughput gains over the conventional UAV-ANOMA scheme.

The computational complexity of conventional user pairing methods increases quadratically with the number of users because all possible user combinations must be evaluated. In contrast, the proposed MLP-based framework performs pairing through a single forward pass of the trained neural network. Consequently, the complexity is significantly reduced, making the proposed approach suitable for dense UAV-assisted NOMA networks with large numbers of users. Table II presents the comparison for different schemes.

TABLE II
Computational Complexity Comparison

Method	Complexity
Conventional NOMA Pairing	$\mathcal{O}(N^2)$
UAV-NOMA Pairing	$\mathcal{O}(N^2)$
Proposed MLP-Based Pairing	$\mathcal{O}(N)$

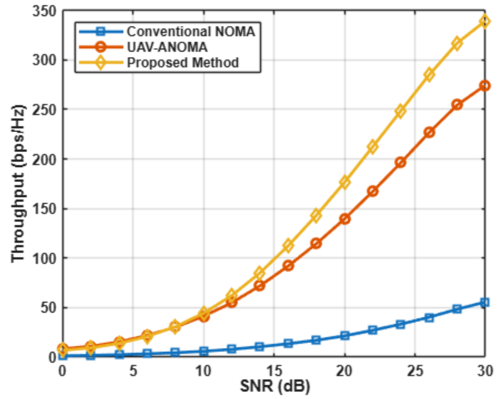

Fig. 2. Throughput Comparison of Conventional NOMA, UAV-ANOMA and Proposed MLP-Based UAV-ANOMA

V. Conclusion

In this paper, a deep learning-based user pairing framework for UAV-assisted non-orthogonal multiple access systems was developed. The proposed approach employs a MLP model to intelligently identify suitable user pairs based on channel conditions and user locations, thereby reducing the complexity associated with conventional optimization-based pairing methods. By exploiting the favorable air-to-ground propagation characteristics of UAV communications and integrating a learning-driven pairing strategy, the proposed framework enhances resource utilization and overall network performance. Simulation results demonstrated that UAV-ANOMA achieves superior throughput performance compared with conventional NOMA due to improved channel quality, enhanced line-of-sight connectivity, and reduced propagation loss. Furthermore, the proposed MLP-based pairing scheme consistently outperformed both benchmark systems by efficiently selecting users with complementary channel characteristics.

The computational complexity analysis further revealed that the proposed learning-based framework significantly reduces the processing burden compared with traditional exhaustive search and optimization approaches. As a result, the proposed scheme offers a scalable and practical solution for dense wireless networks with a large number of users, enabling efficient real-time implementation. Overall, the integration of deep learning with UAV-assisted NOMA provides an effective mechanism for improving throughput, fairness, and scalability in next-generation wireless communication systems. Future research may extend this work by incorporating UAV trajectory optimization, adaptive power allocation, user mobility considerations, and advanced learning architectures such as graph neural networks and reinforcement learning models to further improve network performance under dynamic wireless environments.

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