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AI-Aided Height Optimization for NOMA-UAV Networks

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***Abstract*—Currently, Unmanned Aerial Vehicles (UAVs) are gaining significant attention due to their potential to effectively carry out a variety of tasks with superior performance through the use of fifth-generation (5G) and sixth-generation (6G) networks. Non-orthogonal multiple access (NOMA) techniques can further improve the performance and efficiency while reducing the interference. In this paper, we propose the application of machine learning (ML) techniques to evaluate the outage performance of a NOMA-enabled UAV network. Specifically, this study investigates the optimal UAV height that allows two users on the ground to receive the best service when they are simultaneously served by one UAV. We generated our own dataset which included several network parameters. We then trained various machine learning techniques on this dataset, including artificial neural networks (ANN), support vector regression (SVR), and linear regression (LR). Our results indicate that ANN provides the best accuracy compared with SVR and LR, with an average root mean squared error (RMSE) of 0.0931.**

***Index Terms*—Unmanned aerial vehicles (UAVs), artificial intelligence (AI), non-orthogonal multiple access (NOMA), machine learning (ML).**

I. INTRODUCTION

The utilization of non-orthogonal multiple access (NOMA) techniques is becoming increasingly necessary to support the rising number of connections and data traffic in fifth-generation and beyond (B5G) networks [1]. As a potential solution, the incorporation of Unmanned Aerial Vehicles (UAVs) into NOMA networks has been proposed, where the UAV and the base station (BS) cooperate to serve ground users [2], [3].

NOMA-based UAVs can support emergency communication network architectures. Disaster areas can be categorized into three main areas; emergency areas, large areas, and densely populated areas. Equipped with antenna arrays, UAVs can provide wireless coverage to a large number of widely distributed devices in a disaster area [4]. On the one hand, the current time-division multiple access (TDMA) techniques and other inefficient orthogonal multiple access (OMA) techniques may not be able to accommodate a huge number of users in future communication scenarios. Contrary to OMA, NOMA makes use of successive interference cancellation (SIC) technology to let numerous users share the same resource block at various power levels [5]–[7].

Additionally, it has been observed that machine learning (ML) has become one of the most sought-after fields in the modern era, allowing machines to gain intelligence and process tasks more efficiently than humans. Consequently, ML has been utilized in a range of applications more often than previously expected [8]–[10]. In order to handle numerous wireless communication difficulties, including those linked to UAVs, deep learning (DL), reinforcement learning (RL), federated learning (FL), and other branches of artificial intelligence (AI) have also evolved. By using layers of artificial perceptrons, DL simulates the human mind. In contrast to DL, RL is frequently used in robots for complicated task learning and path planning. It is also employed in a variety of decision-making issues where an agent with a goal interacts with a particular environment. Additionally, to facilitate data-decentralized network systems, FL; which Google proposed in 2016 [11], was created. On devices that share decentralized data, it secures a highly centralized model being trained without moving the data to a local shared unit. Particularly, it runs several ML algorithms across distributed data infrastructure.

As a result, using AI to solve different UAV-related difficulties is a crucial solution to such challenges because AI offers several benefits [12]. Although traditional methods have been effective in addressing these issues, their solutions are still quite elaborate, require more time, and have lower accuracy. Additionally, ML-assisted trajectory planning makes it possible to equip UAVs with the right battery capacity so they may avoid obstacles and plan their routes on their own, supporting more clients and extending battery life. For instance, ”follow me” drones have recently experienced tremendous market success. Therefore, the utilization of ML approaches to automate difficult tasks related to UAVs and to intelligently enhance the overall system efficiency can significantly improve the network performance of the UAV system as a whole.

The utilization of artificial neural networks (ANNs) has been considered beneficial for constructing a system model with high accuracy and minimal complexity, even in the presence of uncertainties and disturbances. Furthermore, it makes the implementation easier and improves the real-time performance [13]. In [14], the optimization of user power allocation and UAV location was undertaken jointly in order to maximize both energy efficiency and coverage rate. Subsequently, K-means clustering was used to separate the ground users into clusters, with each UAV serving a single cluster. To improve the UAV capabilities of diverse applications, ML techniques, including support vector regression (SVR), linear regression (LR), and ANN have been used to analyze remote sensing data collected by UAVs. In this paper, we investigate the potential of utilizing various ML techniques to improve the performance of UAV services in a NOMA-UAV network. Specifically, we analyze the NOMA-UAV network parameters to predict the optimal UAV height using different ML techniques. The paper is organized as follows: Section I discusses UAVs, NOMA, and the use of ML techniques in this area. Section II presents our proposed system model and its mathematical analysis. Section III introduces our channel model that is used in the proposed system. Section IV highlights the ML algorithms that have been used throughout this paper. Section V presents our performance evaluation. Finally, Section VI concludes the paper.

II. Proposed System Model

In this section, we describe our NOMA-UAV system model that can predict the optimum height of a UAV to enhance the users' services using different ML algorithms. Our system, shown in Figure 1, is based on the consideration of a single UAV-enabled system and two NOMA users communicating with the UAV (represented by $U1$ and $U2$). A UAV has a flying altitude h, the radius of a circular trajectory r, and a constant velocity v. The UAV position is given with its angle position ϕ, so the UAV location is introduced as $(rcosj, rsinj, h)$. Because of that, the Euclidean distance between the UAV and users $U1$ and $U2$, can be calculated as in [15].

$$\bar{d_1} = \sqrt{h^2 + r^{+} L^2 - 2rLcos\phi} \tag{1}$$

$$\bar{d_2} = \sqrt{h^2 + r^{+} L^2 + 2rLcos\phi} \tag{2}$$

A UAV is used to establish communication between two users (i.e., U_1 and U_2) as an air base station. For each Monte Carlo sample, users are randomly distributed in a 2D region (x-axis and y-axis). While the UAV has a flight path randomly defined at points in a circle in a 3D region (x-axis, y-axis and z-axis). U_1 is viewed as the primary user, and U_2 is viewed as the secondary user. To guarantee the primary user's quality-of-service (QoS) requirements, the UAV first decodes the U_1's message. Then, the UAV decodes the message from the secondary user U_2 without experiencing any performance degradation to the primary user. To meet users' QoS needs, different levels of power coefficients must be assigned to each user's signal. Performance indicators include achievable rate and outage probability.

$P_{LoS}(\Theta_k)$ and $P_{NLoS}(\Theta_k) = 1 - P_{LoS}(qk)$ indicate the probability of line-of-sight (LoS) and non-line-of-sight (NLoS), respectively. Using the following formula, these final two values are determined as in [16].

$$P_{LoS}(\Theta_k) = \frac{1}{1 + pe^{-q(\Theta_k - q)}} \tag{3}$$

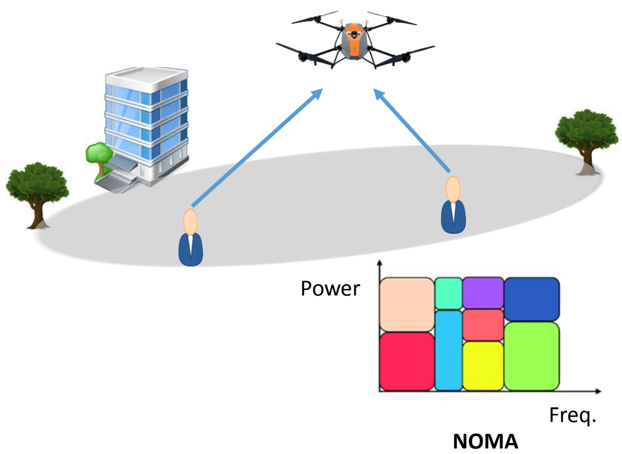

Fig. 1. UAV with NOMA system model.

where p and q are constant values depending on the environment and $(\Theta_k) = arcsin(h/d_k)$ is the elevation angle of the UAV with respect to each user where h is the height of the UAV [17]. Fading is modeled by Rician distribution:

$$s = \sqrt{\frac{K}{(K+1) * P_{LOS}}} \tag{4}$$

$$\sigma = \sqrt{\frac{P_{LOS}}{2 * (K+1)}} \tag{5}$$

where K is the Rician fading, s is the mean, $alpha$ is the path loss exponent, and σ is the standard deviation. The signal-to-interference plus noise-and-distortion ratio (SINDR) at U_1 can be calculated by

$$S\bar{N}R = \frac{w_2 P\bar{d_1}^{-\alpha} SNR_1}{N_0 + P\bar{d_1}^{-\alpha} SNR_1[h_{iU}{}_2^2 w_2 + (1 + h_{iU}{}_1^2) w_1]}, \tag{6}$$

$$P = \frac{\sigma_A^2}{T} \int_0^T P^2(t)dt, \tag{7}$$

where $W = 2\pi F$ is the bandwidth related to the system, and $F = \frac{1}{T}$ is the operating frequency. Then, for U_2, this can be calculated as

$$S\bar{N}R = \frac{w_2 P\bar{d_2}^{-\alpha} SNR_1}{N_0 + P\bar{d_2}^{-\alpha} SNR_2[h_{iU}{}_2^2 w_2 + (1 + h_{iU}{}_1^2) w_1]}, \tag{8}$$

where $SNR_1 = \mid \bar{h_1} \mid^2$ and $SNR_2 = \mid \bar{h_2} \mid^2$ as $\bar{h_1}$ and $\bar{h_2}$ are hardware impairment factors.

III. Channel Model

It is anticipated that large-scale route loss and small-scale fading will occur on the wireless channels between UAVs and ground users. The Rician distribution can be utilized to model the Line-of-Sight LoS and multipath scatterers at the ground receiver for a UAV-to-ground connection channel, as a trustworthy LoS route being accessible is a common characteristic of this type of link channel. For the unordered squared channel gain's probability distribution function (pdf), a non-central chi-square distribution with two degrees of freedom γ_i is utilized, where $i \in 1, 2$ [18].

$$f_{|\gamma_i|^2}(x) = e^{K_i} e^{-\phi_i x} \sum_{q=0}^{\infty} \frac{K_i^q \phi_i^{k+1}}{q! \Gamma(q+1)} x^q \quad (9)$$

where $x = \sum_{k=1}^{M} \sqrt{pk} sk$, pk is the power allocated to user k and sk is the transmitted signal of $k^t h$ user,
in which $G(x)$ is the gamma function. The CDF (cumulative distribution function) is written as

$$f_{|\gamma_i|^2}(x) = 1 - Q(\sqrt{2K_i}, \sqrt{2\phi_i x}) \quad (10)$$

A. Outage Probability Calculations

The outage probability (OP) of a network under the effects of LoS and NLoS propagation for U_1 is determined as

$$\begin{aligned} OP_{U1} = 1 - [P_{LOS}(\theta_1) \int_{X_{max}^{-}}^{\infty} f_{\gamma 1}(x) dx \\ + P_{NLOS}(\theta_1) \int_{X_{max}^{-}/w}^{\infty} f_{\gamma 1}(x) dx] \end{aligned} \quad (11)$$

$$\begin{aligned} OP_{U1} = 1 - [P_{LOS}(\theta_1)[1 - f_{\gamma 1}(x_{max})] \\ - P_{NLOS}(\theta_1)[1 - f_{\gamma 1}(\frac{\bar{x}_{max}}{w})] \end{aligned} \quad (12)$$

in which $w = 1$ for LoS propagation and $w < 1$ for NLoS propagation as in [19], and $\bar{x}_{max} = max(\bar{x_1}, \bar{x_2})$, where

$$\bar{x_1} = \frac{\bar{Tr_1}}{\rho {d_1}^{-\alpha}[w_1 - \bar{Tr_1}[k^2{}_{U2} w_2 + k^2{}_{U1} w_1]]}, \quad (13)$$

$$\bar{x_2} = \frac{\bar{Tr_2}}{\rho {d_1}^{-\alpha}[w_2 - \bar{Tr_2}[k^2{}_{U2} w_2 + (1 + k^2{}_{U1}) w_1]]}, \quad (14)$$

where $\rho = \frac{P}{N_0}$, and $Tr_i = 2^{2R_i} - 1$, $i \in (1, 2)$, as Tr is the transmission rate.

B. Throughput Analysis

We can calculate throughput for the users as in [20] as follows.

$$\bar{\tau_i} = (1 - OP_{Ui}) T_i, i \in (1, 2), \quad (15)$$

where T_i is the throughput for each user.

IV. ML Schemes and Terminologies

Numerous research works, including [21]–[24], have discussed various ML techniques. However, we quickly review the ML schemes used in this paper.

For UAV applications, standard classification models such as support vector machines (SVM), K-nearest neighbors (KNN), and decision trees (DT) can be used [25]. Additionally, the latest powerful graphics processing unit (GPU) designs provide highly advanced artificial neural networks (ANN) trained on big datasets [22], [24]. We briefly highlight the key ideas of the ML schemes as we design parameters to predict the best height of the UAV as the output where $\bar{\tau_i}$, OP, and U_1, U_2 positions are the inputs, that we use in the paper as follows:

- **Support Vector Regression (SVR)**: To predict discrete values, support vector regression, a supervised learning technique, is employed. The way it works is similar to how a support vector machine (SVM) works. The core idea of SVR is to locate the best-fit line. The SVR best-fitting line is the hyperplane with the most points. The line's equation is similar to that of linear regression, $y = wx + b$, [21].
- **Linear Regression (LR):** Regression analysis builds a mathematical relationship between two or more variables based on observational data to investigate the underlying principles of the data. Predicting the value of a dependent variable, (y), based on an independent variable, (x), is carried out via linear regression. As a result, the linear relationship between $x(input)$ and $y(output)$ is discovered using the regression technique. The linear regression model is established if the sample data demonstrates that the two are in agreement with the linear relationship: $y = a + bx$, where y is the dependent variable, a is the constant term, b is the regression coefficient, x is the independent variable. We apply a linear regression technique in our system to predict the optimum height for UAV to provide users' best service.
- **Artificial Neural Networks (ANN):** An artificial neuron is able to transmit signals to other neurons connected to it, once it has processed the input signals. The sum of the inputs to the neuron, where the value of the message at each link is a real number, is used to determine a nonlinear function that is responsible for determining the output of the neuron. Connections between neurons are referred to as edges. During the process of learning, the weights of neurons and edges change recurrently. Additionally, neurons can be equipped with a threshold, which must be surpassed in order for the neuron to be able to transmit a signal. We use ANN model with two hidden layers to predict the best height of the UAV.

The average root mean squared error (RMSE) is an effective metric for assessing the accuracy of numerical predictions and for determining the quality of the regression line fit to the data points. Additionally, it is applicable to ANN models. The formula for calculating RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}} \quad (16)$$

where, $Predicted_i$ is the predicted value for the ith observation. $Actual_i$ is the observed value for the ith observation. N is the total number of observations.

V. Performance Evaluation

In this section, we will present our system results with different ML models. Firstly, we generated dataset that had been used to train different models by using the equations in our system models as we put ranges for all parameters and threshold values for parameters as best values, then generated the dataset. The parameters we used are as follows, a number of users $= 2$, $R_1 = 1.5$, $R_2 = 1$, $w_1 = 0.1$, $w_2 = 0.9$, $\bar{h_1} = \bar{h_2} = 0.1$, $\alpha = 2$, $\phi = 0$, $p = 4.886$, and $q = 0.429$.

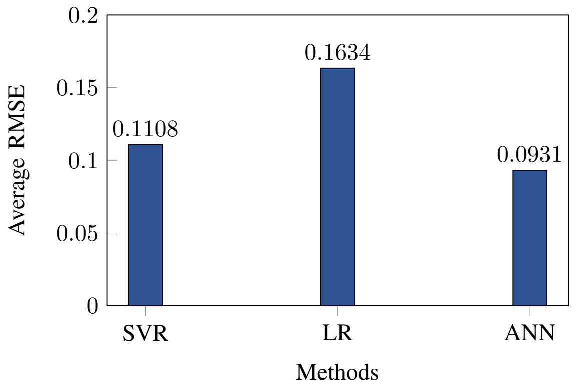

Fig. 2. Comparison between the proposed ML models to show the average RMSE for each model.

- **Dataset:** To generate our dataset to train different ML models, we used equations that appeared in the proposed system model in Section II as we use the parameters' values as follows. $SNR = [10, 60]dB$, user radius [1,20]m, UAV radius [1,5]m, UAV height [50, 200]m. Then, we generate 1000 scenarios for NOMA-UAV with two users and train our model to predict the best height.
- **SVR:** After applying SVM on our system, as shown in Fig. 2, an average RSME of height prediction of 0.1108 was obtained.
- **LR:** For the LR results, we calculated the average RMSE to be 0.1634, as shown in Fig. 2.
- **ANN:** When ANN is used in our system to enhance the accuracy of the optimal height prediction, as shown in Fig. 2, we calculate the average RMSE as 0.0931 which is the best performance (i.e., lowest average RSME) that we could achieve in our system with its specific parameters.

VI. Conclusion

In this paper, we investigated a system comprising one unmanned aerial vehicle (UAV) and two users in order to evaluate its parameters and proposed different machine learning (ML) techniques to predict the optimal height of the UAV that provides the best service to the users. The results revealed that the artificial neural network (ANN) technique yielded the lowest average root mean squared error (RMSE) of 0.0931, compared with 0.1108 for support vector regression (SVR) and 0.1634 for linear regression (LR). As a future direction, we intend to increase the number of UAV parameters to enhance the system and render a more reliable service.

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