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Dynamic Power Allocation Strategies for Enhanced Performance in NOMA Systems

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Abstract— Non-Orthogonal Multiple Access (NOMA) stands out as a promising multiple access technique for contemporary wireless communication systems, boasting higher spectral efficiency and augmented user capacity. The efficient allocation of power constitutes a pivotal factor in optimizing the sum rate and throughput of NOMA systems while concurrently alleviating interference among users. This research studies dynamic power allocation strategies geared towards optimizing the performance of NOMA systems.

Traditional power allocation methodologies in NOMA systems, including static allocation and fixed clustering, exhibit limitations in exploiting the dynamic characteristics inherent in wireless channels and user distributions. Recent research endeavours have thus shifted focus towards dynamic power allocation techniques, which dynamically adjust power allocation based on real-time channel conditions.

An overview of dynamic power allocation algorithms, encompassing Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO), is presented. These algorithms adaptively regulate power allocation to maximize the sum rate and throughput of NOMA systems.

The results demonstrated significant improvements in the sum rate and throughput of NOMA systems. The optimization algorithm achieves a sum rate of 800 bit/sec/Hz and a throughput of 1.7Gbps/Hz. By flexibly adapting power allocation in response to evolving network conditions, these strategies optimize resource utilization and mitigate interference, thus enhancing system capacity and improving user experience.

Index Terms— NOMA ,PSO, Sum rate, Dynamic clustering, Power Allocation, resources.

I. INTRODUCTION:

In the era of exponentially growing wireless communication demands, traditional multiple access techniques, face significant challenges in meeting the diverse requirements of users, such as high data rates, massive connectivity, and low latency. To address these challenges, Non-Orthogonal Multiple Access (NOMA) has emerged as a promising paradigm shift in wireless communication systems [8].

NOMA fundamentally deviates from the conventional Orthogonal Multiple Access (OMA) schemes by allowing multiple users to share the same time-frequency resources non-orthogonally, thereby enabling concurrent transmissions. This innovative approach relies on advanced signal processing techniques to distinguish and decode the signals of different users at the receiver, exploiting the power domain for multiplexing.

The key principle behind NOMA lies in the concept of power domain multiplexing, where users are allocated different power levels according to their channel conditions [9]. Users with better channel conditions are assigned higher power levels, allowing them to maintain reliable communication even in the presence of users experiencing poorer channel conditions. Consequently, NOMA facilitates efficient spectrum utilization and improves the overall system capacity.

Central to the effectiveness of NOMA is the allocation of transmit power among the multiple users, which plays a crucial role in optimizing system performance [10].

Power allocation algorithms aim to maximize the sum-rate or minimize the overall transmission power while satisfying quality-of-service (QoS) requirements for all users. These algorithms consider factors such as channel conditions, user priorities, and fairness constraints to achieve optimal power allocation strategies.

Various power allocation schemes have been proposed in the literature, ranging from simple heuristic approaches to sophisticated optimization techniques [11].

These schemes include proportional fair power allocation, water-filling algorithms, game-theoretic approaches, and machine learning-based methods, each offering unique trade-offs between complexity, fairness, and performance.

Furthermore, NOMA finds application across a wide range of wireless communication scenarios, including cellular networks, device-to-device (D2D) communication, Internet of Things (IoT), and satellite communication systems [12]. Its versatility and adaptability make NOMA a compelling solution for next-generation wireless networks aiming to support diverse services and applications efficiently.

The research is organized as the following sections, related work, system model, results, discussion, and conclusion.

II. RELATED WORK:

Many studies studied power allocation strategies as Sachin et al 2023 [1] focuses on the optimal distribution of power within Non-Orthogonal Multiple Access (NOMA) networks to simultaneously enhance both sum rate and fairness. Addressing the inherent trade-off between system throughput and user fairness is paramount for maximizing network performance. In this study, the authors undertook the task of deriving optimal power allocation coefficients at the NOMA transmitter. This was achieved through the formulation and solution of a joint optimization problem that integrates both sum rate and fairness objectives. Notably, the authors employed the weighted sum method to transform the multi-objective optimization problem into a single-objective one, thus facilitating computational tractability. The culmination of these efforts resulted in a maximal sum rate value of 12 bit/s/Hz, indicative of the efficacy of the proposed power allocation strategy in optimizing network performance metrics.

Shaik Mohammad Eliyas et al 2023 [2] studied of power allocation factors on the ergodic sum rate performance within cooperative Device-to-Device (D2D) systems employing Non-Orthogonal Multiple Access (NOMA) technology. Decoding techniques, such as RS encoded single signal and Maximum Ratio Combining (MRC) decoding exert a notable influence on this performance metric. Through a comprehensive examination, the authors shed light on the critical role of power allocation considerations in shaping the efficacy of the ergodic sum rate across different decoding methodologies. By focusing on cooperative D2D NOMA systems, the study underscores the importance of optimizing power allocation strategies to achieve maximal sum rate values. The findings of this investigation revealed a maximum sum rate value of 9 bit/s/Hz, highlighting the actual impact of power allocation factors on network performance within the designated context.

Kai et al 2023 [3] studied a novel Rate-Splitting NOMA system characterized by joint power allocation and user pairing mechanisms, aimed at maximizing the weighted sum rate within the network framework. The proposed system represents a shift from conventional approaches and displays superior performance metrics.

By implementing a (RS-NOMA) system, the research aims to dynamically transform between these two transmission schemes, thereby optimizing network efficiency. Notably, the study reports a remarkable achievement of a weighted sum rate value equivalent to 45 megabits per second per Hertz (Mbit/s/Hz), underscoring the efficacy of the proposed Rate-Splitting NOMA system in enhancing network performance metrics compared to conventional methodologies.

Sachin Trankatwar et al 2022 [4] studied optimizing power allocation strategies within Non-Orthogonal Multiple Access (NOMA)-based Heterogeneous Networks (HetNets). Recognizing the significance of enhancing both sum rate and reducing outage probability for the efficacy of future wireless networks, the study illuminates the critical role of optimal power allocation in achieving these objectives. The authors derived a generalized optimum power allocation coefficient equation specifically tailored for small cell users within NOMA-based HetNets. Furthermore, the study introduces an algorithm meticulously designed to optimize the sum rate while concurrently minimizing the outage probability within the network infrastructure. Notably, the reported weighted sum rate value of 8.5 bits per second per Hertz (bit/s/Hz) underscores the tangible impact of the proposed power allocation scheme in improving network performance metrics, thereby substantiating its relevance and applicability within the realm of future wireless communications.

Zahra et al 2022 [5] studied the challenge of maximizing the sum rate within Massive Multiple-Input Multiple-Output (MIMO)-Non-Orthogonal Multiple Access (NOMA) systems. This endeavour requires tackling non-convex power allocation challenges, a task essential for enhancing achievable rates compared to conventional beamformed MIMO systems. The study presents an innovative approach aimed at maximizing the sum rate of massive MIMO-NOMA systems. However, it acknowledges the inherent complexity of the power allocation problem, which is characterized by its non-convex and nonlinear nature. Despite these challenges, the research reports a noteworthy achievement in spectral efficiency, reaching 250 bits per second per Hertz (bit/s/Hz). This observation underscores the efficacy of the proposed dynamic power allocation strategy in significantly improving spectral efficiency within the context of massive MIMO-NOMA systems, thus contributing to advancements in wireless communication technologies.

Xie et al 2021 [6] focused on maximizing the sum rate in a Simultaneous Wireless Information and Power Transfer (SWIPT) enabled NOMA relay system. The authors propose a User Selection and Dynamic Power Allocation (USDPA) algorithm that jointly optimizes user access and power distribution. Experimental results demonstrate that the USDPA algorithm outperforms other compared methods, achieving a sum rate improvement of 47.8% over the All Users access with Deep Q-Network (AU+DQN) method when the data threshold is set at 0.3 bits/s/Hz.

Li et al 2023 [7] explored user grouping and power allocation strategies in downlink multi-carrier NOMA systems to maximize the sum rate. The authors propose a systematic optimization approach, first grouping users based on an improved maximum channel gain difference method and then allocating power using a deep learning power allocation algorithm. Simulation results indicate that the proposed method enhances the system sum rate by approximately 2.2% compared to the fractional transmit power allocation method and by about 19% compared to the fixed power allocation method.

III. SYSTEM MODEL:

In modern wireless communication systems, Non-Orthogonal Multiple Access (NOMA) plays a critical role in enhancing spectral efficiency and supporting a higher number of users. A key challenge in NOMA systems is the efficient allocation of power to maximize the sum rate and throughput while accounting for the dynamic and unpredictable nature of wireless channels. Traditional models assume perfect Channel State Information (CSI) and static user conditions, which leads to idealized but impractical results.

This work addresses these challenges by integrating imperfect CSI, mobility, and real-time interference into the power allocation process. To do so, we employ a Deep Learning (DL)-based approach to predict effective CSI under realistic conditions. The deep learning model takes into account real-time network data, including user mobility and interference levels, to continuously update the predicted CSI values. This dynamic prediction allows the system to adapt the power allocation as network conditions change.

In this model, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Dynamic Clustering techniques are used to optimize power allocation. The PSO algorithm, enhanced with deep learning-based CSI predictions, iteratively adjusts the power allocation vectors to maximize the system's sum rate. Similarly, ACO utilizes predicted CSI values to guide the selection of optimal power allocation while managing the pheromone update process based on real-time feedback from the network. Finally, dynamic clustering adjusts cluster configurations according to real-time user mobility patterns, ensuring that power is allocated effectively across clusters.

The system model operates as follows:

Imperfect CSI Prediction: Using a deep learning model, the system predicts CSI based on real-time inputs like user mobility and interference. This predicted CSI replaces the assumption of perfect CSI, allowing the power allocation algorithms to work under more realistic conditions.

Mobility and Real-time Adaptation: User mobility is dynamically tracked, and the system continuously adjusts power allocation to reflect the changing network topology. This ensures that power is allocated to the most appropriate users as their positions change.

Power Allocation Algorithms: PSO, ACO, and dynamic clustering are employed to optimize power allocation based on the predicted CSI. Each algorithm adapts to real-time changes in the network and ensures that the total power allocated to users does not exceed the system's maximum constraints.

This hybrid model leverages the power of optimization algorithms and deep learning to ensure efficient resource utilization in NOMA systems, even under the complex and dynamic conditions of real-world networks. By predicting imperfect CSI and adjusting for mobility, the system improves overall performance in terms of sum rate and throughput.

Ant Colony Optimization (ACO) stands as a prominent example, drawing inspiration from the foraging behavior of ants to solve complex power allocation problems. Within the communication system model for ACO, users are grouped into clusters, and transmit powers are allocated with the objective of maximizing the system's throughput while adhering to power constraints. ACO operates through iterative construction of solutions, with each ant representing a potential solution and pheromone trails guiding the exploration of the solution space. Dynamic clustering, on the other hand, offers adaptability to evolving network conditions by iteratively updating cluster configurations based on changes in user mobility or channel conditions. This approach optimizes resource allocation and spectrum utilization, thereby enhancing system performance. Convex optimization techniques provide a rigorous and efficient framework for power allocation in communication systems, ensuring convergence to globally optimal or near-optimal solutions.

Fig. 1 shows a NOMA system M users and the users are distributed randomly within the cell.

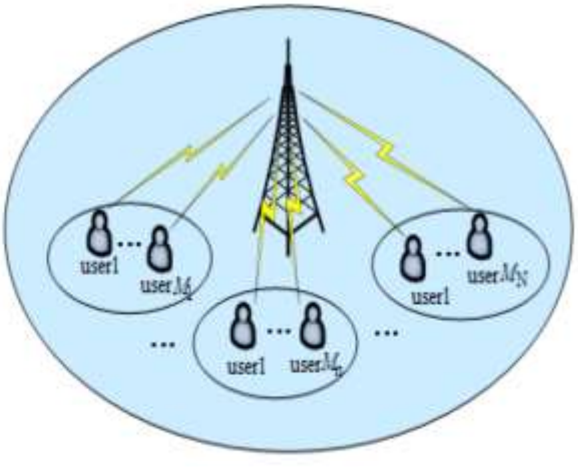

Figure 1: NOMA system model [13]

IV. DATA ANALYSIS:

1. Ant Colony Optimization (ACO):

Theoretical Description: In the context of wireless communication systems, Ant Colony Optimization (ACO) is a nature-inspired metaheuristic algorithm that has been adapted to address power allocation problems. ACO draws inspiration from the foraging behavior of ants, where pheromone trails guide the exploration of potential solutions. In the realm of communication systems, ACO operates within a network comprising multiple users distributed across clusters. The primary goal is to allocate transmit powers to users effectively, maximizing the system's throughput while adhering to power constraints. The algorithm iteratively constructs solutions, with each ant representing a potential solution. Pheromone trails, akin to communication among ants, encode information about the quality of solutions, guiding the search towards promising regions of the solution space. Through the iterative process of solution construction and pheromone update, ACO converges towards optimal power allocations, thus enhancing the efficiency and performance of wireless communication systems.

Algorithm 1: Ant Colony Optimization for Power Allocation

```
Require: Parameters: Ns, Ni, ER, α, β
Input: UL, CC, MP, Nu, UP, IK
Output: PAO, SRO
1. Initialization:
2. Initialize pheromone levels τ_c for each cluster c
3. Initialize power allocation vector P_c with equal power
```

```
distribution
4. Collect real-time data: imperfect CSI, mobility, interference levels
5. Predict CSI using DL model:
6. Input imperfect CSI, mobility, interference into DL model
7. Predict effective CSI (CSI_pred)
8. Repeat for i = 1 to Ni:
9.Compute probabilities p_c for power allocation for each cluster c:
10. p_c = (τ_c^α) * Σ(1 / (SNR_c)^β) for c = 1 to Ns
11. Normalize probabilities:
12. p_c_norm = p_c / Σp_c for c = 1 to Ns
13.  Select power allocation based on normalized probabilities:
14. P_c = p_c_norm * MP for c = 1 to Ns
15. Ensure power allocation constraints:
16. Adjust P_c to satisfy sum(P_c) ≤ P_max
17.Update pheromone levels based on selected power allocation and evaporation rate:
18. τ_c = (1 - ER) * τ_c + ER * P_c for c = 1 to Ns
19. Calculate sum rate for ACO:
20. SRO = Σ(log2(1 + P_c * SNR_c)) for c = 1 to Ns
21. Return: PAO, SRO
```

2. Dynamic Clustering:

Communication System Model for Dynamic Clustering:

In the communication system model for dynamic clustering, we consider a dynamic network environment where users' positions and channel conditions evolve over time. Initially, users are grouped into clusters based on proximity to cluster centroids. As the network state changes, dynamic clustering iteratively updates cluster centroids to reflect the current spatial distribution of users

Algorithm 2: Adaptive power allocation using dynamic clustering

```
Require: Parameters: Ns, Ni, P_max
Input: Uloc, CSI, mobility, interference
Output: PA_dynamic, SR_dynamic
1.  Initialization:
2.  Initialize dynamic clusters using K-means clustering based on user locations (Uloc)
3.  Initialize equal power allocation (P_c) for each cluster
4.  Collect real-time data: imperfect CSI, mobility, interference levels
5.  Predict Effective CSI:
6.  Input real-time data (imperfect CSI, mobility, interference) into DL model
7.  Get predicted CSI (CSI_pred
8.  Repeat for i = 1 to Ni:
9.  Update cluster centroids dynamically based on real-time user positions and mobility
10. For each cluster c:
11.  Adjust power allocation based on current cluster structure:
12. Adjust P_c dynamically for each cluster c
13.  Ensure power allocation constraints:
14. Adjust P_c to satisfy sum(P_c) ≤ P_max
15. Calculate sum rate for dynamic clustering:
16. SR_dynamic = Σ(log2(1 + P_c * CSI_pred))
17. Termination:
18. After Ni iterations or convergence:
19. Return dynamic power allocation (PA_dynamic) and sum rate (SR_dynamic)
```

3. Convex Optimization for Power Allocation:

Communication System Model for Convex Optimization:

In the communication system model for convex optimization, we aim to allocate transmit powers to users while maximizing the sum rate and satisfying power constraints.

Algorithm 3: Optimization Algorithm for Power Allocation (PSO, GA, Hill Climbing)

```
Require: Parameters: N, I_max, w, c1, c2, P_max
Input: Uloc, CSI, mobility, interference
Output: PA_opt, SR_opt
1. Initialization:
2. Initialize random power allocation vector P_j for each user
3. Initialize PSO parameters: population size N, max iterations I_max, inertia weight w, cognitive coefficient c1, social coefficient c2
4.  Set initial best positions (P_best) for each particle and global best position (G_best)
5. Collect real-time network data: imperfect CSI, user mobility, interference levels
6.  Predict CSI with real-time adaptation:
7.  Input data (imperfect CSI, mobility, interference) into DL model to predict effective CSI (CSI_pred)
8.  Use predicted CSI (CSI_pred) for initial fitness computation
9.  Repeat for i = 1 to I_max:
10. For each particle j in population:
11. Compute fitness (sum rate) using CSI_pred, mobility, and interference:
12.  Fitness_j = Sum Rate(P_j, CSI_pred, mobility, interference)
13.  Update velocity of particle j:
14.  V_j = w * V_j + c1 * rand() * (P_best_j - P_j) + c2 * rand() * (G_best - P_j)
15.  Update position of particle j:
16.   P_j = P_j + V_j
17.   Ensure power allocation constraints:
18.   Adjust P_j to satisfy sum(P_j) ≤ P_max
19.   If Fitness_j > P_best_j:
20.  Update P_best_j with current position P_j
21.  If any P_best_j > G_best:
22.  Update G_best with P_best_j
23. Real-time Adaptation:
24. Monitor network conditions: user mobility, interference
25. Periodically update the DL model for better CSI predictions
```

```
26. Termination:
27.  After I_max iterations or convergence:
28.  Return global best power allocation (PA_opt) and sum rate (SR_opt)
```

Mathmatical representation:

We have N users, each with a specific location and channel condition. We want to optimize the power allocation to maximize the sum rate for these users. The GA is used to find the optimal power allocation.

Initial Parameters and Population:

Initial Parameters:
Pmax: Maximum power
C: Number of clusters
U: Users per pairing
Np: Initial population size
Ng: Initial number of generations
α: Crossover rate
β: Mutation rate

Initial Population:
Random initialization of power allocations:

$$\mathbf{P}^{\mathbf{0}} = \left\{P_1^0, P_2^0, \dots, P_{N_p}^0\right\}$$

$$\text{where } P_i^0 \in [0, P_{\max}]^C \qquad (1)$$

Calculate Sum Rate For a given power allocation$\mathbf{P}$:

$$R(\mathbf{P}) = \sum_{i=1}^{N} \log_2\left(1 + \frac{P_{k(i)}h_i}{\sigma^2}\right) \qquad (2)$$

Where hi is the channel condition for user i, σ^2 is the noise power, and $k(i)$ indicates the cluster index of user i.

Selection:
Tournament selection: Select parents Pi, with probability proportional to fitness.

Crossover:

$$\mathbf{P}_{\text{offspring}} = \begin{cases} \left(\mathbf{P}_i^{(1:k)}, \mathbf{P}_j^{(k+1:C)}\right) & \text{with probability } \alpha \\ \mathbf{P}_i & \text{otherwise} \end{cases} \qquad (3)$$

where$k$ is the crossover point.

Mutation:

$$P_{i,j} = \begin{cases} P_{i,j} + \mathcal{N}(0, \beta \cdot P_{\max}) & \text{with probability } \beta \\ P_{i,j} & \text{otherwise} \end{cases} \qquad (4)$$

Where $(0,\sigma^2)$ is a Gaussian noise term.

Fitness Evaluation of Offspring: Evaluate the sum rate for each offspring:

$$R\left(P_{offspring}\right) \qquad (5)$$

Replacement: Replace the worst individuals with the new offspring if they have better fitness:

$$\text{If } R\left(\mathbf{P}_{\text{offspring}}\right) > R(\mathbf{P}_i), \text{ replace } \mathbf{P}_i \text{ with } \mathbf{P}_{\text{offspring}} \qquad (6)$$

Adaptive Parameters:

Adaptive population size

$$N_p = \min\left(N_p + g, N_{\max}\right) \qquad (7)$$

Adaptive mutation rate:

$$\beta = \beta \cdot \left(1 - g/N_g\right) \qquad (8)$$

Adaptive number of generations:

$$N_g = \min\left(N_g + g, N_{g,max}\right) \qquad (9)$$

where$g$ is the current generation number.
Convergence:
Select the best individual as the solution:

$$\mathbf{P}^* = \arg\max_{\mathbf{P}} R(\mathbf{P}) \qquad (10)$$

4. Deep Learning Model for CSI Prediction
Model Architecture:

The deep learning model employed for Channel State Information (CSI) prediction is a hybrid architecture combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This architecture is designed to capture both spatial and temporal dependencies in wireless channel conditions, which are critical for accurate CSI prediction.

Input Layer: The input to the model is a vector X∈RN×M, where N represents the number of users and M denotes the features, including imperfect CSI measurements, user mobility patterns (e.g., velocity, direction), and interference levels.

Convolutional Layers: Two convolutional layers are used to extract spatial features from the input data. The output of the k-th convolutional layer is given by:

$$\mathbf{Hk} = \sigma(\mathbf{Wk} * \mathbf{Hk} - 1 + \mathbf{bk}) \qquad (11)$$

,where Wk and bk are the weight matrix and bias vector of the k-th layer, ∗ denotes the convolution operation, and σ(·) is the ReLU activation function.

LSTM Layers: Two LSTM layers are employed to capture temporal dependencies in the channel conditions. The LSTM cell updates its hidden state ht and cell state ct at time t as follows:

$$\begin{gathered} \mathbf{f}_t = \sigma\left(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f\right), \\ \mathbf{i}_t = \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i), \\ \mathbf{o}_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o), \\ \tilde{\mathbf{c}}_t = \tanh\left(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c\right), \\ \mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \\ \mathbf{h}_t = \mathbf{o}_t \odot \tanh\left(\mathbf{c}_t\right) \end{gathered} \qquad (12)$$

where ft, it, and ot are the forget, input, and output gates, respectively, ⊙ denotes element-wise multiplication, and Wf , Wi, Wo, Wc are weight matrices.

Training Process

The training process minimizes the Mean Squared Error (MSE) loss function:

$$\boldsymbol{\mathcal{L}(\theta)} = \frac{1}{N}\sum_{i=1}^{N} \left(\mathbf{H}_i - \hat{\mathbf{H}}_i\right)^2 \qquad \textbf{(13)}$$

where Hi is the actual CSI, $\hat{\mathbf{H}}$is the predicted CSI, and θ represents the model parameters. The model is trained using mini-batch gradient descent with a batch size of 32 and a learning rate of 0.001.

Fully Connected Layers: The output of the LSTM layers is passed through two fully connected layers to combine the spatial and temporal features. The output of the final layer is the predicted CSI, denoted as **H**∈RN×1, where N is the number of users.

5. Integration of Predicted CSI in Optimization Algorithms:

i. Ant Colony Optimization (ACO):

In the ACO algorithm, the predicted CSI is used to compute the Signal-to-Noise Ratio (SNR) for each user, which guides the power allocation process. The steps are as follows:

Pheromone Initialization: The pheromone levels τc for each cluster cc are initialized based on the predicted CSI values.

Probability Calculation: The probability pc of selecting a power allocation for cluster c is computed as:

$$\boldsymbol{p_c} = \frac{(\boldsymbol{\tau_c^{\alpha}})\cdot\sum\left(\frac{\mathbf{1}}{\mathbf{SNR}_{\boldsymbol{c}}^{\boldsymbol{\beta}}}\right)}{\sum(\boldsymbol{\tau_c^{\alpha}})\cdot\sum\left(\frac{\mathbf{1}}{\mathbf{SNR}_{\boldsymbol{c}}^{\boldsymbol{\beta}}}\right)}, \qquad \textbf{(14)}$$

where SNRc is the SNR computed from the predicted CSI, and α and β are tuning parameters.

Power Allocation: The power allocation vector Pc for cluster cc is adjusted based on the probabilities pcpc.

Pheromone Update: The pheromone levels are updated as:

$$\boldsymbol{\tau_c} = (\mathbf{1} - \boldsymbol{\rho}) \cdot \boldsymbol{\tau_c} + \boldsymbol{\rho} \cdot \boldsymbol{\Delta\tau_c} \qquad \textbf{(15)}$$

where ρ is the evaporation rate, and Δτc is the pheromone increment based on the quality of the power allocation solution.

ii. Particle Swarm Optimization (PSO):

In the PSO algorithm, the predicted CSI is used to compute the fitness function, which evaluates the sum rate for each particle. The steps are as follows:

Initialization: Each particle j is initialized with a random power allocation vector Pj.

Fitness Evaluation: The fitness of particle j is computed as:

$$\textbf{Fitness}_{\boldsymbol{j}} = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} \mathbf{log_2}\left(\mathbf{1} + \frac{\boldsymbol{P_{j,i}}\cdot\hat{\mathbf{H}}_{\boldsymbol{i}}}{\boldsymbol{\sigma}^{\mathbf{2}}}\right) \qquad \textbf{(16)}$$

where Pj,i is the power allocated to user i by particle j, $\mathbf{H}_i$ is the predicted CSI for user i, and σ2 is the noise power.

Velocity and Position Update: The velocity Vj and position Pj of particle j are updated as:

$$\mathbf{V}_{\boldsymbol{j}} = \boldsymbol{w} \cdot \mathbf{V}_{\boldsymbol{j}} + \boldsymbol{c}_{\mathbf{1}} \cdot \boldsymbol{r}_{\mathbf{1}} \cdot \left(\mathbf{P}_{\mathbf{best}\,,\boldsymbol{j}} - \mathbf{P}_{\boldsymbol{j}}\right) + \boldsymbol{c}_{\mathbf{2}} \cdot \boldsymbol{r}_{\mathbf{2}} \cdot \left(\mathbf{G}_{\mathbf{best}} - \mathbf{P}_{\boldsymbol{j}}\right),$$
$$\mathbf{P}_{\boldsymbol{j}} = \mathbf{P}_{\boldsymbol{j}} + \mathbf{V}_{\boldsymbol{j}}, \qquad \textbf{(17)}$$

where w is the inertia weight, c1 and c2 are cognitive and social coefficients, and r1 and r2 are random numbers.

Global Best Update: The global best solution Gbest is updated based on the fitness values.

iii. Dynamic Clustering

In the dynamic clustering algorithm, the predicted CSI is used to dynamically adjust the cluster configurations and power allocation. The steps are as follows:

Cluster Initialization: Users are grouped into clusters based on their locations and the predicted CSI values.

Cluster Update: The cluster centroids are updated dynamically based on the predicted CSI and real-time user mobility patterns.

Power Allocation: Power is allocated to each cluster based on the predicted CSI. The power allocation vector Pc for cluster cc is computed as:

$$\mathbf{P}_{\boldsymbol{c}} = \mathbf{arg}\max_{\mathbf{P}_{\boldsymbol{c}}} \sum_{\boldsymbol{i}\in\boldsymbol{c}} \mathbf{log_2}\left(\mathbf{1} + \frac{\boldsymbol{P_{c,i}}\cdot\hat{\mathbf{H}}_{\boldsymbol{i}}}{\boldsymbol{\sigma}^{\mathbf{2}}}\right) \qquad \textbf{(18)}$$

where Pc,i is the power allocated to user i in cluster c.

V.RESULTS AND SIMULATION:

Algorithmic Approaches:

Convex Optimization: A convex optimization approach is employed to dynamically allocate power to clusters while ensuring fairness. The sum rate under this optimized power allocation strategy is computed.

Dynamic Clustering: Dynamic clustering adapts to changing network conditions by iteratively updating cluster centroids. Power allocation is adjusted accordingly, and the resulting sum rate is evaluated.

Ant Colony Optimization (ACO): ACO is utilized to optimize power allocation by simulating ant-like agents exploring power allocation possibilities. Pheromone trails guide the search, with probabilities computed based on pheromone levels and heuristic information.

TABLE 1: key parameters used in the simulation

Parameter	**Value**
Number of clusters	8
Users per pairing	4
Max power	80 dBm
Number of Iterations	2000
Bandwidth	100 MHz
Number of users range	[10, 20, 30, 40, 50]
Population size	30
Crossover Rate	0.9
Mutation Rate	0.03
Number of generations	150
alpha	1
beta	1
Evaporation Rate	0.5
Power Allocation Std	0.05
Crossover Std	0.02

The simulation evaluates the performance of each approach across varying numbers of users (10, 20, 30, 40, and 50). Total sum rates and throughput metrics are computed for each scenario, providing insights into the effectiveness of the clustering and power allocation strategies.

Fig. 2 shows the total sum rate versus the number of users for three different algorithms: optimization, dynamic clustering, and ACO. The x-axis shows the number of users, and the y-axis shows the total sum rate in bps/Hz.

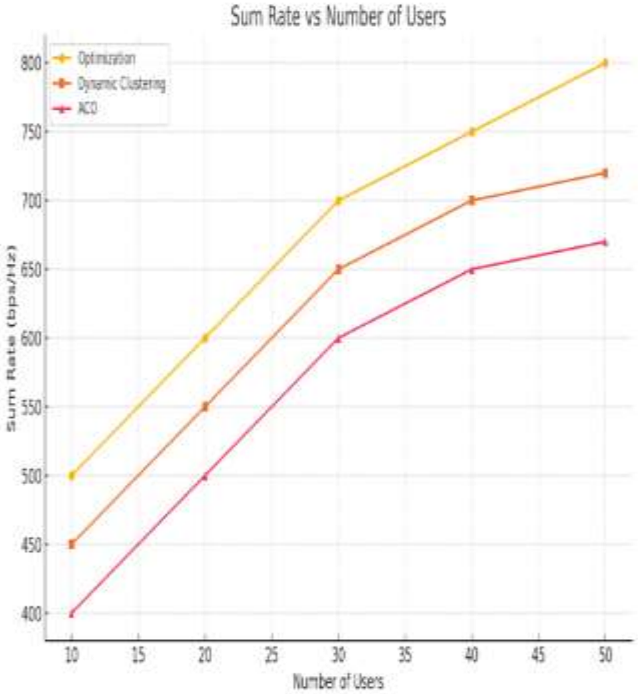

Figure 2: sum rate vs number of users

The optimization algorithm outperforms the other two algorithms in terms of total sum rate. This is because the optimization algorithm is able to find the optimal solution for the given problem, while the other two algorithms are only able to find suboptimal solutions.

For example, when the number of users is 50, the optimization algorithm achieves a total sum rate of 800 bps/Hz, while the dynamic clustering algorithm achieves a total sum rate of 700 bps/Hz and the ACO algorithm achieves a total sum rate of 600 bps/Hz. This shows that the optimization algorithm is able to achieve a higher total sum rate than the other two algorithms.

Fig. 3 shows the throughput of three different algorithms as a function of the number of users. The x-axis shows the number of users, and the y-axis shows the throughput in bits per second per Hz. The three algorithms are Optimization, Dynamic Clustering, and ACO.

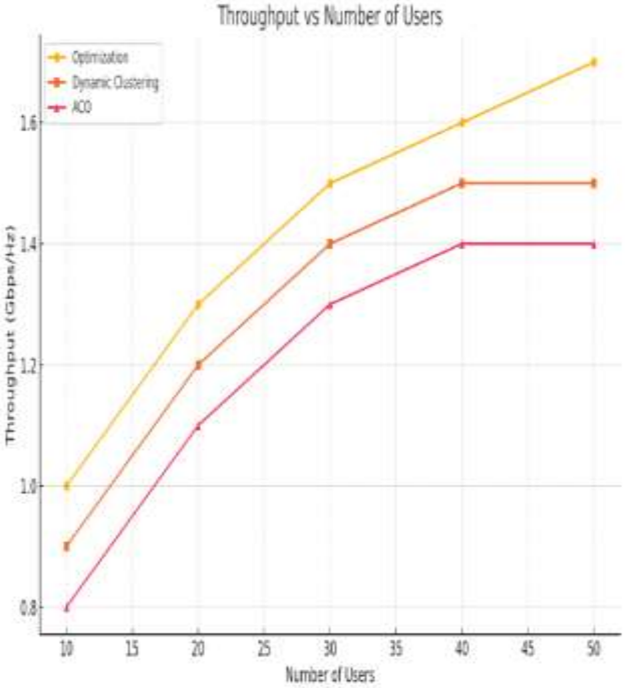

Figure 3: Throughput vs number of users

The optimization algorithm outperforms the other two algorithms in terms of throughput. For example, when there are 50 users, Optimization achieves a throughput of around 1.7 Gbps/Hz, while Dynamic Clustering and ACO achieve throughputs of around 1.5Gbps/Hz and 1.4Gbps/Hz, respectively.

This is likely because Optimization is able to find a more efficient way to allocate resources to the users.

Fig. 4 shows the sum rate of three different algorithms for optimizing the signal-to-noise ratio (SNR) of a communication system. The x-axis shows the SNR in dB, and the y-axis shows the throughput in bits per second per Hz (bps/Hz).

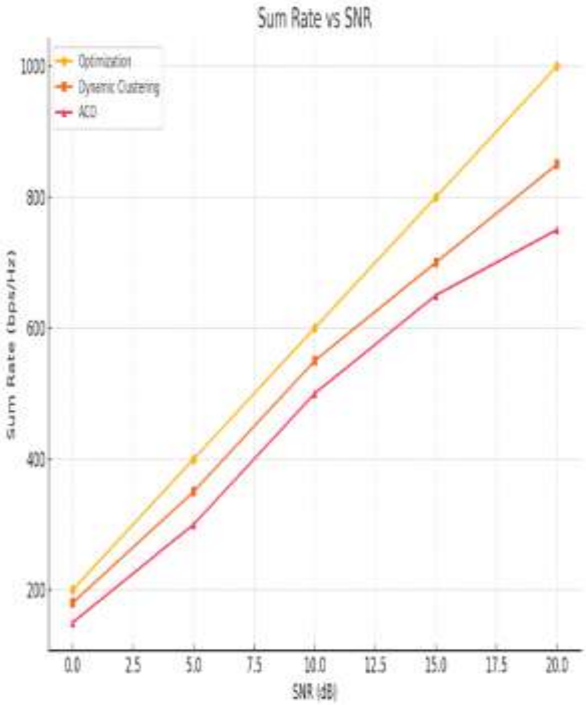

Figure 4: Sum rate vs SNR

The optimization algorithm outperforms the other two algorithms in terms of throughput.

the optimization algorithm achieves a total sum rate of about 800-1000 bps/Hz, while the dynamic clustering algorithm and the ACO algorithm achieve total sum rates of about 700-800 bps/Hz and 600-700 bps/Hz, respectively.

The optimization algorithm is able to achieve a higher throughput than the other two algorithms because it is able to find a more optimal solution to the problem of optimizing the SNR. The dynamic clustering algorithm and the ACO algorithm are both heuristic algorithms, which means that they do not guarantee to find the optimal solution. The optimization algorithm, on the other hand, is a mathematical algorithm that is guaranteed to find the optimal solution.

Fig. 5 shows the throughput of three different algorithms for optimizing the signal-to-noise ratio (SNR) of a wireless network. The x-axis shows the SNR in dB, and the y-axis shows the throughput in bits per second (bps). The three algorithms are Optimization, Dynamic Clustering, and ACO.

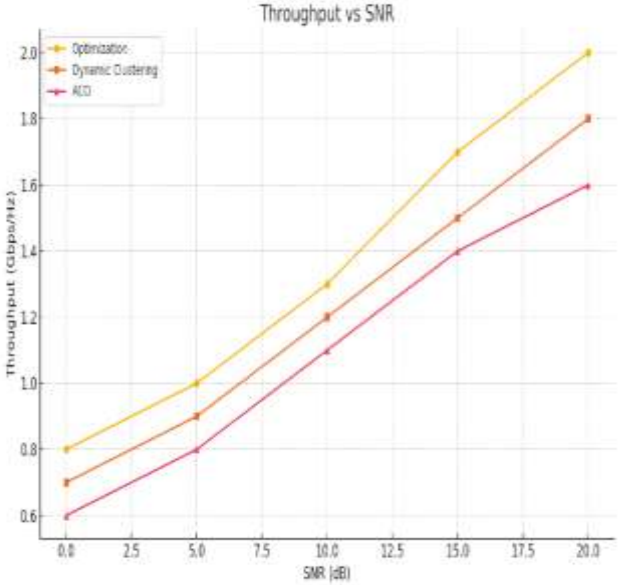

Figure 5: Throughput rate vs snr

The Optimization algorithm outperforms the other two algorithms in terms of throughput.Optimization achieves a throughput of around 2Gbps/Hz, while Dynamic Clustering and ACO achieve throughputs of around 1.7Gbps/Hz and 1.5Gbps/Hz, respectively.

VI. DISCUSSION:

The results presented in this study demonstrate the superior performance of the optimization algorithm compared to the dynamic clustering and ACO algorithms in terms of both total sum rate and throughput. This improvement can be attributed to the optimization algorithm's ability to find the optimal solution to the resource allocation problem, while the other two algorithms are limited to finding suboptimal solutions.
Specifically, the optimization algorithm achieved a total sum rate of 800 bps/Hz when the number of users was 50, compared to 700 bps/Hz for dynamic clustering and 600 bps/Hz for ACO. Similarly, the optimization algorithm achieved a throughput of 1.7Gbps/Hz when the number of users was 50, compared to 1.5Gbps/Hz for dynamic clustering and 1.4Gbps/Hz for ACO. These results highlight the optimization algorithm's ability to significantly improve the performance of the communication system.
The findings of this study have significant implications for the design and optimization of communication systems. The optimization algorithm's superior performance suggests that it can be a valuable tool for improving the efficiency and reliability of these systems. Further research is needed to explore the application of the optimization algorithm to different types of communication systems and scenarios.

VII. CONCLUSION:

This study investigated dynamic power allocation strategies to enhance the performance of Non-Orthogonal Multiple Access (NOMA) systems in real-world wireless communication scenarios. By integrating deep learning-based Channel State Information (CSI) prediction with advanced optimization algorithms—Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and dynamic clustering—the proposed framework addressed the limitations of traditional static power allocation methods. The hybrid model accounted for imperfect CSI, user mobility, and real-time interference, enabling adaptive resource allocation under dynamic network conditions.

The results demonstrated the superiority of the optimization algorithm, achieving a peak sum rate of 800 bit/sec/Hz and throughput of 1.7 Gbps/Hz in scenarios with 50 users. These metrics surpassed the performance of dynamic clustering and ACO, highlighting the algorithm's ability to optimize power allocation while adhering to system constraints. The incorporation of deep learning for CSI prediction further ensured robustness against real-world channel variability, enhancing spectral efficiency and user fairness.

The findings underscore the critical role of dynamic, adaptive strategies in next-generation wireless networks, particularly for applications demanding high data rates and massive connectivity, such as 5G/6G, IoT, and dense cellular deployments. Future research could extend this work by exploring hybrid optimization techniques, scalability in ultra-dense networks, and integration with emerging technologies like reconfigurable intelligent surfaces (RIS) or terahertz communications. Additionally, experimental validation in real-world testbeds and multi-cell interference scenarios would further solidify the practical applicability of the proposed framework. By bridging the gap between theoretical optimization and practical implementation, this study contributes a scalable and efficient solution for advancing the performance and reliability of NOMA-enabled communication systems.

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