American International Theism University Scientific Research Journal (AITUSRJ)
ISSN (E): 2578-3882**, ISSN (P):** 2578-3874

10.63094/AITUSRJ.25.4.1.6

A Novel Approach for User Clustering In mmWave Non-Orthogonal Multiple Access System

Mohammed Nafl Al Dawsari
King Abdulaziz University,
Jeddah, KSA
maldawsari0017@stu.kau.edu.sa

Abstract – Non-Orthogonal Multiple Access (NOMA) systems require user clustering to optimize resource allocation. In this paper, a clustering approach is developed to group users in Millimeter Wave Non-Orthogonal Multiple Access (mmWave-NOMA) systems. The proposed approach follows five main steps: data preparation, distance estimation, Signal-to-Interference-and-Noise Ratio (SINR) calculation, data combination, and normalization. To cluster users into optimal groups, a novel version of the K-means algorithm that incorporates both distance and SINR values is employed. The Bayesian Information Criterion (BIC) is utilized to determine the optimal number of clusters. The performance of the proposed method is evaluated based on the overall achievable sum rate. Experimental results show that the proposed method achieves a sum rate of 3 bps/Hz when the transmission power is set to 30 dBm and the number of users is 50, and 2.6 bps/Hz when the number of users is 500, respectively, indicating its effectiveness.

Index Terms – mmWave-NOMA, K-means Clustering, Hierarchical Clustering, Unsupervised Machine Learning.

I. INTRODUCTION

With the emergence of next-generation wireless networks, the capacity of a single base station to manage a greater number of devices is expected to increase significantly. These devices demand seamless connectivity due to their exponential traffic consumption. Future networks are evolving towards highly concentrated user bases and managing large volumes of traffic. By the end of 2025, the number of Internet of Things (IoT) devices worldwide is projected to exceed 27 billion [1]. Over the past decade, the surge in mobile communication and traffic has created a proportional demand for more bandwidth [2]. Fifth-generation (5G) cellular networks have enabled a wide range of business applications, and the forthcoming sixth-generation (6G) networks are expected to facilitate advanced intelligent communications [3]. 6G promises higher user density, lower latency, improved efficiency, faster transmission speeds, and increased network capacity. Millimeter-wave (mmWave) communications, operating between 30 and 300 GHz, provide the 5G network with the high bandwidth needed for faster data transfer and minimal interference, supporting highly directional transmission and spectrum propagation [4].

To ensure seamless connectivity for bandwidth-intensive mobile applications, mobile networks continually evolve, designing new multiple access standards. These standards aim to support high data rates with improved energy and spectrum efficiency. Innovative techniques have already been deployed in 5G networks to enhance spectral efficiency and transmission rates [5]. The conventional orthogonal multiple access (OMA) technology, used in 4G networks, cannot simultaneously accommodate the large number of users anticipated in 5G systems. Non-Orthogonal Multiple Access (NOMA) has been proposed to address this limitation by allowing multiple users to share the same orthogonal resources simultaneously [6]. NOMA enhances spectral efficiency by enabling several users to occupy the same resource blocks, thereby supporting higher data rates and broad connectivity in mmWave-NOMA transmissions. In NOMA, multiple power levels (power-domain NOMA) or codes (code-domain NOMA) are assigned to users for simultaneous message transmission or reception [7]. To manage interference, users with stronger channels apply successive interference cancellation (SIC) to decode and remove signals from weaker users. Additionally, NOMA improves user fairness and flexibility in scheduling broadcasts [8], and can enhance the security and efficiency of wireless communications [9]. The mmWave-NOMA system is characterized by the highly directional transmission of mmWave, which facilitates strong channel correlation among users and enables efficient NOMA integration. Additionally, the application of NOMA principles within this system aims to achieve higher capacity and broader connectivity. Together, these characteristics significantly enhance the overall performance and advantages of mmWave-NOMA systems. Sharing beams among multiple users can lead to intra-beam and inter-beam interference. To mitigate inter-beam interference, users within the same beam should have highly correlated channel gains, while users across different beams should have low correlation [10]. Addressing extraordinary traffic demands can be achieved by partitioning the network into smaller clusters. Various clustering approaches exist depending on user data and network requirements.

However, user clustering always involves trade-offs. Random clustering methods often yield suboptimal results, whereas exhaustive search methods, while optimal, become computationally infeasible for moderate to large user populations. Therefore, it is essential to evaluate clustering algorithms in terms of achievable sum rate and scalability with increasing user numbers [11]. Machine learning provides an effective solution for rapid clustering, leveraging the high dimensionality of user information [12]. Furthermore, exploiting the underlying structure of channel information can lead to the development of effective knowledge discovery algorithms. Suboptimal strategies, such as matching theory-based user scheduling, can also mitigate computational complexity [13]; however, these studies often overlook the learning capability. Machine learning algorithms, particularly those incorporating adaptive learning features, offer enhanced performance for mmWave-NOMA systems. Unsupervised learning, especially clustering, is a widely recognized machine learning approach. Using unlabeled datasets, unsupervised clustering algorithms identify inherent data structures and group individuals based on similarity [14]. Clustering ensures that data points within the same cluster are similar, while those in different clusters are dissimilar. The structure of the feature space strongly influences the clustering process [15]. The objective of this paper is to develop a user clustering approach tailored for mmWave-NOMA systems. Specifically, we consider a system where user locations are distributed according to a Poisson cluster process (PCP). The base station (BS) is assumed to have complete channel state information (CSI) for all users and employs superimposed NOMA signals across each beamforming vector. The primary objective is summarized as follows:

To develop an unsupervised user clustering approach using a modified K-means algorithm that optimizes the sum rate for mmWave-NOMA systems. The remainder of this paper is organized as follows: Section II reviews related literature on user clustering techniques for mmWave-NOMA systems. Section III presents the spatial distribution model and system assumptions. Section IV details the data preparation steps. Section V describes the unsupervised clustering methodology. Section VI defines the overall sum rate as the evaluation metric, and Section VII presents the simulation results. Finally, Section VIII concludes the paper.

II. RELATED WORK

One of the challenges in solving optimization problems for user clustering in live networks is the need for numerous computational steps to reach a clustering decision. Performing such clustering with millisecond-level precision, as required by beyond 5G technologies, becomes overly complex if based on instantaneous user channels [16]. This challenge has motivated the exploration of machine learning techniques as viable solutions for user clustering in NOMA systems. Among the most commonly used clustering techniques are Density-Based Spatial Clustering of Applications with Noise [17], K-means, and hierarchical clustering, with the selection of the algorithm depending on the nature of the data and system requirements [18]. Unsupervised clustering methodologies have been widely adopted to address user clustering in mmWave-NOMA systems, as reported by Cui et al. [9], Marasinghe et al. [19], Ren et al. [20], and Shahjalal et al. [21]. Shahjalal et al. [21] categorized clustering approaches into two main groups: joint resource-aware user clustering, which utilizes cosine similarity metrics, and learning-assisted clustering algorithms. Their survey revealed that, despite advancements, most existing clustering approaches suffer from significant runtime complexity, particularly as network size increases. Nevertheless, machine learning-based clustering algorithms, such as K-means, offer reduced complexity compared to conventional optimization methods. Marasinghe et al. [19] employed agglomerative hierarchical clustering to distribute users within a cell. A key advantage of this approach is that it does not require prior knowledge of the number of clusters, addressing the challenges posed by the stochastic distribution of users. Their results demonstrated that hierarchical clustering outperforms K-means in terms of sum-rate optimization in NOMA systems. Elsayed and Erol-Kantarci [13] enhanced the clustering-based service assignment in mmWave-NOMA 5G networks by integrating DBSCAN with online clustering and deep Q-learning. By dynamically assessing user distributions, their strategy produced superior coverage and throughput compared to the baseline K-means clustering. Cui et al. [9] proposed an online K-means clustering algorithm for dynamic scenarios characterized by the continuous arrival of new users. Their comparison indicated that online K-means significantly improved efficiency over conventional static clustering methods in dynamic environments. Hamedoon et al. [14] applied an iterative optimization framework for joint power allocation and user clustering. They introduced a partial brute-force search strategy to reduce the computational burden associated with exhaustive search methods. Further, they employed Lagrange multipliers and Karush-Kuhn-Tucker conditions for optimal power distribution, and leveraged deep neural networks to enhance resource distribution efficiency. Rajasekaran et al. [22] developed a framework where users report their successive interference cancellation (SIC) decoding capabilities to the base station. They formulated the user clustering and ordering problem (UCOP) and proposed the NOMA-minimum exact cover (NOMA-MEC) heuristic, which optimizes cluster assignments while considering SIC capabilities. They also introduced the low-complexity NOMA-best beam (NOMA-BB) strategy. Simulation results showed that both approaches outperformed OMA and conventional NOMA clustering in overall throughput. Later, Rajasekaran et al. [23] and Sokun et al. [24]

addressed the cluster assignment problem using a computationally efficient two-stage artificial neural network (ANN) model. The ANN, trained offline using simulation datasets, efficiently assigned users to clusters based on their CSI and SIC capabilities without burdening base station resources. Simulation results demonstrated that ANN-based clustering schemes achieved performance levels comparable to computationally intensive heuristics. Hoang et al. [4] proposed an ST-DBSCAN spatiotemporal clustering approach that leveraged users' geographic similarities in real-world deployments. Additionally, they utilized boundary-compressed particle swarm optimization to reduce inter-cluster interference and maximize system performance, demonstrating that mmWave-NOMA outperforms mmWave-OMA systems in terms of achievable sum rates. Ren et al. [20] introduced an Expectation-Maximization (EM)-based clustering technique, initially targeting fixed-user scenarios and later extending it to dynamic environments involving user mobility, additions, and removals. Their online EM-based method efficiently tracked distribution parameters, achieving comparable performance to full re-clustering with significantly reduced computational complexity. In summary, the literature has extensively explored user clustering for mmWave-NOMA systems through both traditional optimization methods and machine learning approaches. A persistent challenge across studies remains the high computational complexity associated with real-time clustering, especially as networks grow in size. Techniques such as K-means, hierarchical clustering, and DBSCAN have proven effective under varying conditions. Building upon this foundation, this paper aims to further develop a clustering approach that improves sum rate performance in mmWave-NOMA environments while maintaining computational efficiency.

A. System Model

Consider a downlink mmWave-NOMA communication system comprising a single base station (BS) equipped with NNN antennas. The BS serves TTT users, each connecting to the BS through one of its antennas. Multiple users can simultaneously communicate with each transmit antenna. Let the set of antennas be denoted as N= {A1, A2, …, AN} and the users as T= {U1, U2, …, UT}. Unlike traditional multiple-input single-output (MISO) systems, the proposed model allows multiple users to communicate with the BS via different antennas simultaneously. Users are grouped into distinct clusters, with each cluster assigned a separate beam for transmission and reception. In line with NOMA principles, successive interference cancellation (SIC) is implemented at the user side, leveraging the differences in their effective channel gains. Furthermore, user locations are modeled according to a Poisson cluster process (PCP). Table 1 summarizes the main notations used in the system model.

TABLE I SUMMARY OF SYSTEM MODEL NOTATIONS

Notations	**Description**
$\boldsymbol{N}$	Number of antennas in the BS.
$\boldsymbol{T}$	Number of users.
${}_{i}\boldsymbol{PP}$	Point process
$\boldsymbol{P}$	Parent point
PR	Parent point process
$\boldsymbol{i}$	Number of clusters
${}_{i}^{p}\boldsymbol{O}$	Offspring point process
$\boldsymbol{DF}(\boldsymbol{x})$	Density function
$\boldsymbol{r_i}$	The radius of the circle around the cluster center
${}_{u}\boldsymbol{CM}$	Channel model vector
$\boldsymbol{TP}$	Total number of paths
$\boldsymbol{DI_u^{e_{u,lo}}}$	Distance between user u and the BS
lo=0	Line-of-sight path
$\boldsymbol{e_{u,lo}}$	Path loss exponent
$\boldsymbol{C_{u,lo}}$	Complex gain of the path lo for the user u
$\boldsymbol{S(\theta_u\ ,lo)}$	Steering vector
BA	Antenna spacing of the BS
W	Wavelength
$\boldsymbol{\theta_{u,lo}}$	Angles of departure
RFi	Radio frequency beamforming vector
Mi	Message transmitted
$\boldsymbol{DS_{i,v}}$	Desired signal vector of cluster i
$\mathbf{P}\boldsymbol{P_{i,v}}$	NOMA power splitting factor vector for cluster i
$\boldsymbol{po_i}$	Power allocation coefficient for cluster i
$\boldsymbol{RS_{\ u}}$	Received signal for u user
$\boldsymbol{V_u}$	Represents the variance

B. Spatial Distribution Model

Recent studies typically assume a uniform user distribution based on a single Poisson point process (PPP). In contrast, this work adopts a more realistic correlated distribution by modeling users with a Poisson cluster process (PCP), enabling natural clustering patterns. Clustering users in such a setup presents significant challenges, even under perfect channel state information (CSI), due to the complex association possibilities across multiple clusters. Therefore, machine learning-based techniques are employed to intelligently and efficiently assign users to appropriate clusters. An illustration of the user distribution under the PCP model is provided in Fig. 1, where the base station (BS) partitions the NOMA region into four areas, each centered around a distinct parent point represented by a black triangle, with users distributed uniformly around these centers.

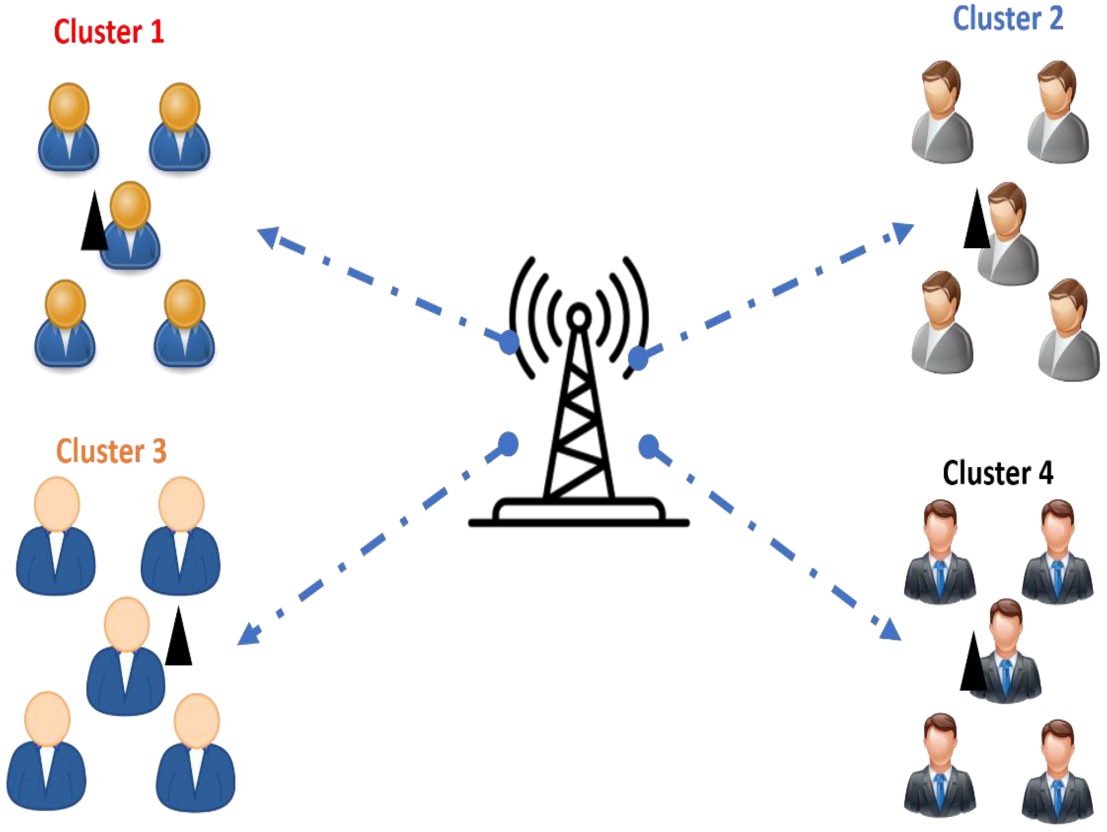

Figure 1 Distribution of users in the mmWave-NOMA system model according to PCP

The point process for cluster i is denoted as PPi and can be calculated as follows:

$$PP_i = \bigcup_{n \in PR} P + O_i^p \tag{1}$$

where p and PR represent the parent point and the process of the parent point, respectively. In this model, the parents are distributed uniformly and considered uncorrelated. O_i^p represents the offspring point process, and each point in O_i^p is distributed identically and independently around the parent point, which belongs to its process PR and has a density function DF(x). The density function for the location of each cluster is related to the location of the cluster center itself. The density function can be expressed as a uniform spatial distribution. The density function DF(x) can be calculated as follows:

$$\mathrm{DF(x)} = \begin{cases} \dfrac{1}{\pi\,(r_i)^2} & if\ \|x\| \le\ r_i) \\ 0 & otherwise \end{cases} \tag{2}$$

where $r_i$represents the radius of the circular region around the cluster center.

Users are thus uniformly distributed within a circular area of radius r_i centered at each parent point. It is important to note that no restriction is imposed on having an equal number of users in each cluster.

C. Channel Model

Millimeter-wave (mmWave) communication channels exhibit a high degree of correlation and are sparsely distributed in the angular domain [25], [26]. The channel model vector for user u, denoted as CM_u, between any user u in the user set T and the base station (BS) under a reliable mmWave transmission model, can be expressed as:

$$CM_u = \sum_{lo=0}^{TP} S(\theta_u\,, lo) \frac{C_{u,lo}}{\sqrt{TP\,(1+\ DI_u^{e_{u,lo}})}} \qquad (3)$$

where TP represents the total number of independent propagation paths, and $DI_u^{(e_{u,l})}$ denotes the distance-dependent path loss between user u and the BS. The index $lo = 0$ corresponds to the line-of-sight (LoS) path. The terms $e_{u,0}$ and $e_{u,lo}$ (for $lo = 1, \dots, TP$) represent the path loss exponents associated with the LoS and non-line-ofsight (NLoS) paths, respectively. Furthermore, $C_{u,lo}$ denotes the complex gain of path lo, and $S(\theta_{u,lo})$ represents the steering vector, which is defined as:

$$S(\theta_u\,, lo) = [1, e^{-\frac{BA}{W} j2\pi \sin(\theta_{u,lo})} \dots., e^{-(M-1)\frac{BA}{W} j2\pi \sin(\theta_{u,lo})}]^T \qquad (4)$$

In this expression, BA is the antenna spacing at the BS , which must satisfy $BA < \frac{W}{2}$, where W is the carrier wavelength. The angle of departure $\theta_{u,lo}$ lies within the range $[0,2\pi]$.

Path loss due to non-line-of-sight conditions is generally greater than that due to line-ofsight conditions in mmWave channels [27]. In fact, the NLoS path loss can be up to 20 dB higher than that experienced in LoS conditions [28]. Therefore, when a LoS path exists, the impact of NLoS links can be considered negligible. Under this assumption, the channel model vector CM_u simplifies to:

$$CM_u = S(\theta_u\,) \frac{C_u}{\sqrt{TP\,(1+\ DI_u^{e})}} \qquad (5)$$

where θ_u and C_u represent the angle of departure and the complex gain of the LoS path, respectively.

D. Signal Model

The base station (BS) can simultaneously transmit M different messages to multiple users using the non-orthogonal multiple access (NOMA) protocol. Let the BS serve a total of U users. The radio frequency (RF) beamforming vector associated with user u, denoted as RF_u, is applied at the BS antennas to create distinct beams capable of transmitting multiple messages concurrently. RF beamforming is realized through analog phase shifters and is assumed to have constant modulus entries. Each beamforming vector RF_u is normalized to satisfy the condition ‖RF_u ‖=1.

The transmitted message intended for user u can be expressed as:

$$M_u = \sum_{u=1}^{U} \sqrt{P_u}\, DS_u \qquad (6)$$

where P_u denotes the transmission power allocated to user u, and DS_u represents the desired signal vector for user u, defined as:

$$DS_u = \sqrt{po_u}\, RF_u \qquad (7)$$

Here, po_u is the power allocation coefficient assigned to user u.

The received signal at user u, denoted as RS_u, can be formulated as:

$$\begin{aligned} RS_u = {} & CC_u^H \sqrt{po_u} RF_u DS_u \\ & + CC_u^H \sqrt{po_u} RF_u \sum_{j=1}^{U} DS_j \\ & + CC_u^H \sum_{j \neq i} M_j + V_u \qquad (8) \end{aligned}$$

where CC_u^H represents the Hermitian transpose of the channel coefficient vector between the BS and user u, and V_u denotes the additive white Gaussian noise (AWGN) at user u.

Within the mmWave-NOMA system, users experience intra-cluster interference caused by simultaneous transmissions from other users within the same cluster. Strong users can eliminate this interference by employing successive interference cancellation (SIC) techniques, while weak users decode their signals directly without using SIC.

However, inter-cluster interference remains a significant challenge, negatively affecting the SIC decoding process. In a downlink NOMA system, the user with the highest channel gain predominantly influences the overall sum rate (Ding et al., 2016).

This work aims to achieve two main objectives:

- To assist users with weak channel gains in meeting their quality-of-service (QoS) requirements.
- To enhance the performance of users with strong channel gains.

By addressing these goals, the proposed method improves the overall system-wide achievable sum rate.

III. METHODOLOGY

A. Data Preparation

Before applying the proposed method, the data is prepared to enhance the performance of the system. Four steps are performed in the data preparation phase: distance estimation, Signal-to-Interference-and-Noise Ratio (SINR) calculation, data combination, and normalization.

In the distance estimation step, the distance between the BS and users is calculated using the Euclidean distance, defined as:

$$ED_u = \sqrt{(u_x - BS_x)^2 + (u_y - BS_y)^2} \quad (9)$$

where u_x and u_y represent the coordinates of the user, and BS_x and BS_y represent the coordinates of the base station.

In the SINR calculation step, the SINR value for each user is estimated based on the channel and received signal efficiency, as follows:

$$SINR_u = \frac{po_u |CC_u^H RF_u|^2}{\sum_{v=1, v \neq u}^{N} \left(po_v |CC_v^H RF_v|^2\right) + V_u} \quad (10)$$

Thus, the Euclidean distance and the SINR value for each user are combined to form the final dataset used in the clustering phase. Finally, a normalization technique is applied to prevent overfitting and to ensure that the clustering algorithm does not favor larger values, which could skew the clustering toward specific clusters.

B. Unsupervised Machine Learning Algorithm

The K-means clustering algorithm is employed to group users into appropriate clusters within the mmWave-NOMA system. This section discusses and presents the K-means algorithm in detail.

K-means Algorithm

K-means is a partitional clustering algorithm that distributes a set of users into non-overlapping subsets (clusters) by measuring the distance between cluster centroids and users. Several steps are applied to utilize K-means in the mmWave-NOMA system. Initially, assuming a fixed number of clusters (C), C points are randomly selected as the initial centroids. The distance between each user and each centroid is then calculated, and each user is assigned to the nearest centroid. Multiple users may be assigned to the same centroid to form a cluster. Subsequently, new centroids are computed by averaging the positions of users assigned to each cluster. The process of user assignment and centroid update is repeated iteratively until convergence, i.e., no further changes occur in cluster assignments or centroids.

In this paper, the K-means algorithm is applied to the normalized dataset prepared in the earlier step. The Euclidean distance metric is used to measure the distance between each user and the cluster centroids. The distance is computed as:

$$D(U_i, C_i) = \sum_{k=1}^{n} (U_{ik} - CE(C_{ik}))^2 \quad (11)$$

where $CE(C_{ik})$ represents the centroid of cluster i along dimension k, and n represents the number of features (dimensions) considered.

Algorithm 1 outlines the steps followed to cluster users based on the Euclidean distance metric.

Algorithm 1: K-means algorithm

```
Input: Normalized Users data (NU), number of users (N), Number of Clusters (C)
Output: Cluster User (CU)
Randomly, BS chooses a set of users as the centroid $CE_u$ for each cluster
Set Final distance FD for all users equal to ∞
Repeat until $CE_k$ doesn't change or objective function OF is achieved
    For i=1 to N do
        For J=1 to C do
            Compute the distance $D(U_i, C_J)$ using $\sum_{k=1}^{n}(NU_{ik} - CE(C_{ik}))^2$
            If $D(U_i, C_J) < FD_i$ do
                $FD_{i=} D(U_i, C_J)$
            End If
        End For
        Cluster the user and store in $CU_i$
    End For
    For k=1 to C do
        Recompute the centroid for each cluster using $CE_k = \frac{1}{|CE_k|} \sum_{i=1}^{k} U_k$
    End For
End Repeat
Return CU
```

The objective function (OF) for the clustering process is defined as the minimum squared error between each user and the centroid of its assigned cluster. It is mathematically expressed as:

$$\min_{c} OF(c) = \sum_{K=1}^{C} \sum_{i=1}^{W} (U_i - CE(C_{ik}))^2 \quad (12)$$

Ident where $\boldsymbol{W}$ denotes the number of users in cluster $\boldsymbol{k}$, $\boldsymbol{C}$ is the total number of clusters, $\boldsymbol{U_i}$ represents the data point of user $\boldsymbol{i}$, and $\boldsymbol{CE(C_{ik})}$ is the centroid coordinate for cluster $\boldsymbol{k}$ in dimension $\boldsymbol{i}$.

Identifying The Appropriate Number of Clusters

To obtain the best clustering performance in K-means, the Bayesian Information Criterion (BIC) is utilized to determine the optimal number of clusters K. The proposed system leverages BIC to avoid overfitting, which may occur when an excessively large number of clusters is selected.

BIC is an effective statistical tool that introduces a penalty for model complexity while evaluating clustering quality. It ensures the best trade-off between the goodness of fit and the simplicity of the clustering model. BIC values are computed for various candidate numbers of clusters, and the number of clusters corresponding to the lowest BIC value is selected as the optimal choice.

Algorithm 2 outlines the BIC-based procedure, where K-means is applied with different cluster numbers, BIC values are calculated, and the optimal cluster count is identified based on the minimum BIC score.

Algorithm 2: Bayesian Information Criterion algorithm

```
Input: Normalized Users data (NU), min number of clusters (Kmin),
       max number of Cluster (Kmax), number of users (N)
Output: optimal number of clusters (K)
Set the BIC matrix for each cluster number to 0
For m=kmin to kmax do
    Apply K-means on m number of cluster and
    Normalized Users data (NU)
    Calculate the sum of the squared distance between each user and cluster centroid
    Calculate the variance of the clusters va$^2$
    Calculate within-cluster variance (WCSS) by summing the squared distances within each cluster.
    Calculate log-likelihood $L = -\frac{N}{2} * \log(2\ \pi\ va^2) - WCSS\ /\ (2\ *\ va^2)$
    Calculate BIC value = $-2\ * \ln L\ +\ k\ * \ln N$
    Add BIC value to BIC matrix

End For
k=Find the location of the minimum BIC value from the BIC matrix
Return CU
```

Evaluation metric

To evaluate the performance of the proposed system, the overall achievable sum rate metric is employed. The sum rate reflects the efficiency and throughput gains achieved by the clustering and resource allocation strategies.

The overall achievable sum rate, denoted as R_{sum}, is computed as:

$$R_{\text{sum}} = \sum_{k=1}^{K} \sum_{v=1}^{U_k} \mathbb{E}\big(\log\big(1 + \text{SINR}_{u,k}\big)\big) \tag{13}$$

where $\mathbb{E}$ denotes the expectation operator, K is the number of clusters, U_k represents the number of users in cluster k, and $\text{SINR}_{u,k}$ is the signal-to-interference-and-noise ratio for user u in cluster k.

The SINR for user u in cluster k is defined as:

$$\text{SINR}_{u,k} = \frac{po_{u,k}\left|CC_{u,k}^{H} RF_{u,k}\right|^2}{\sum_{v=1,v\neq u}^{V_k}\ po_{v,k}\left|CC_{v,k}^{H} RF_{v,k}\right|^2 + \sum_{s=1,s\neq k}^{K}\ po_s\left|CC_s^{H} RF_s\right|^2 + V_u} \tag{14}$$

where:

$\sum_{v=1,v\neq u}^{V_k}\ po_{v,k}\left|CC_{v,k}^{H} RF_{v,k}\right|^2$ accounts for the intra-cluster interference (from other users within the same cluster),

$\sum_{s=1,s\neq k}^{K}\ po_s\left|CC_s^{H} RF_s\right|^2$ accounts for the inter-cluster interference (from users belonging to different clusters),

V_u represents the noise variance at user u.

This metric provides a comprehensive assessment of the system's performance by considering both intra-cluster and inter-cluster interference effects.

IV. SIMULATION RESULTS

The proposed system is evaluated in this section to assess its performance using computer simulations. The channel model utilized follows the formulation shown in Equation (3). Table 2 summarizes the assumptions adopted in the channel model.

The mmWave bandwidth is assumed to be 2 GHz, and the carrier frequency is set to 28 GHz, with a path loss exponent equal to 2. The noise figure (NF) is assumed to be 10 dB, and the noise power is calculated as $\mathbf{-174 + 10\log_{10}}$ (BW) + NF dB. The user distribution follows the Poisson Cluster Process (PCP) method, where parent users are uniformly distributed within a circle of radius $\boldsymbol{R_p = 5}$ meters, and child users are distributed within a smaller circle of radius $\boldsymbol{R_c = 1}$ meter.

TABLE II PARAMETERS AND THEIR VALUES

Parameter	Value
Bandwidth of mmWave (BW)	2 GHz
The frequency of the carrier	28 GHz
Path loss exponent	2
Noise figure (NF)	10 dB
The power of the noise	-174 + 10 log 10 (BW) + NF dB
The radius of the circle where the parent user distributed	5m
The radius of the circle where the parent user distributed	1m

In this study, the Bayesian Information Criterion (BIC) algorithm is utilized to determine the optimal number of clusters K for K-means clustering. As shown in Figure 2, when the number of users is set to 50, the BIC achieves its minimum value at K=2, indicating that two clusters represent the optimal grouping for the user distribution.

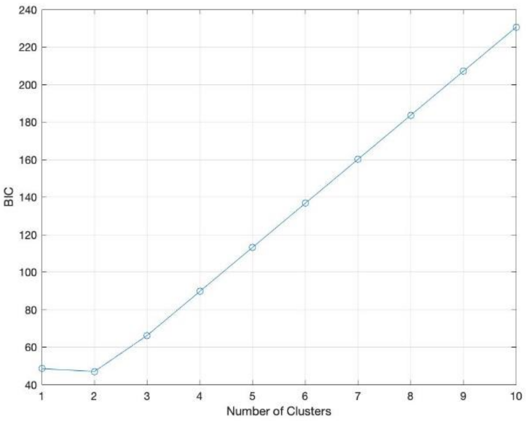

Figure 2 Optimal number of clusters when 50 users are clustered

Fig. 3 also shows that when the number of users increases to 500, the simulation results indicate that the best BIC value is achieved when the number of clusters is 2.

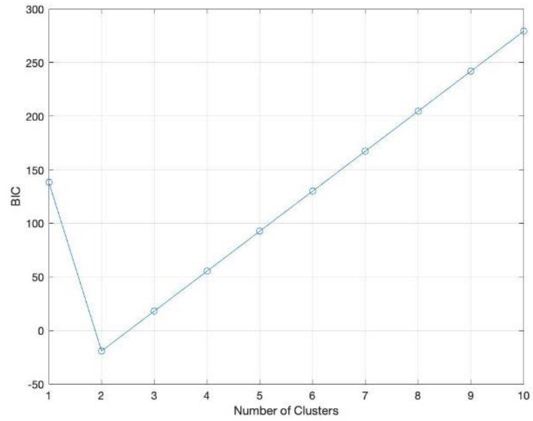

Figure 3 Optimal number of clusters when 500 users are clustered

The overall achievable sum rate is calculated for K-means clustering when 50 users are considered. Figure 4 compares the overall achievable sum rates achieved by K-means when using both SINR and distance features versus using distance only, as the transmission power varies from 0 dBm to 30 dBm.

The results show that in the transmission power range of 0 dBm to 15 dBm, the sum rate achieved by K-means remains approximately equal whether using only distance or both distance and SINR. However, when the transmission power exceeds 15 dBm, the total sum rate achieved by considering both distance and SINR becomes higher than that achieved using distance only.

Figure 4 clearly demonstrates that incorporating both distance and SINR into the K-means clustering process yields superior performance, resulting in a higher overall achievable sum rate compared to using distance alone.

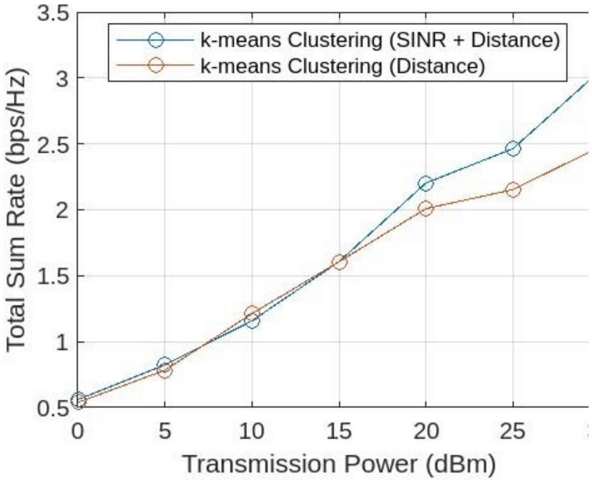

Figure 4 Comparison between the overall sum rate of k-means (SINR + Distance) and k-means (Distance only) when 50 users are clustered

A simulation was also conducted to evaluate the overall achievable sum rate when using distance only versus using both distance and SINR with K-means clustering for 500 users. Figure 5 illustrates that both methods achieve an overall sum rate of approximately 16 bps/Hz when the transmission power is set to 30 dBm. The sum rates for both methods remain nearly equal within the transmission power range of 0 dBm to 25 dBm. However, when the transmission power exceeds 25 dBm, the overall achievable sum rate obtained by K-means using both SINR and distance surpasses that achieved by using distance alone.

This result confirms that incorporating SINR into the clustering process becomes more beneficial at higher transmission power levels, resulting in improved system performance.

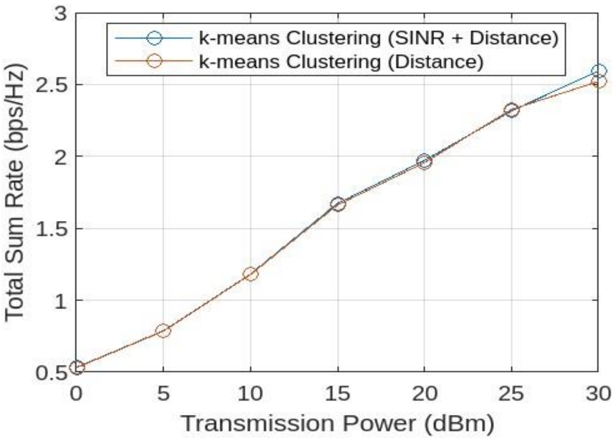

Figure 5 Comparison between the overall sum rate of k-means (SINR + Distance) and k-means (Distance only) when 500 users are clustered

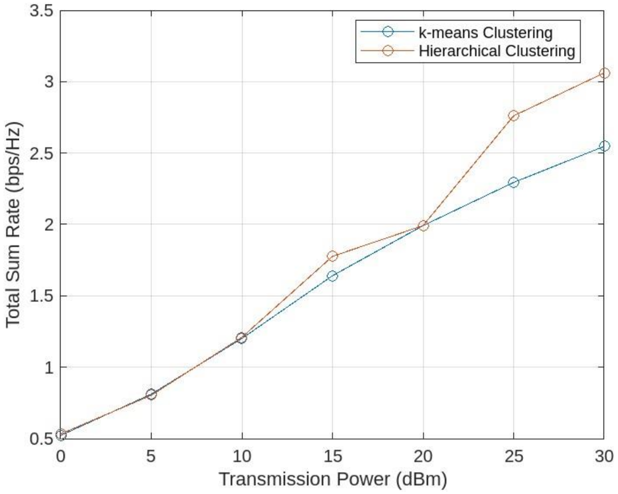

Figure 6 Comparison of total sum rate performance between K-means clustering and hierarchical clustering versus transmission power.

Figure 6 shows a comparison between the total sum rates achieved by K-means clustering and hierarchical clustering across different transmission power levels. Both clustering methods demonstrate similar performance when the transmission power is low, between 0 dBm and 15 dBm. However, as the transmission power increases beyond 20 dBm, hierarchical clustering consistently outperforms K-means clustering. The total sum rate achieved by hierarchical clustering becomes significantly higher, especially at 25 dBm and 30 dBm. This result highlights the potential benefits of adopting hierarchical clustering in mmWave-NOMA systems, particularly under high transmission power conditions, where maximizing the sum rate becomes critical.

V. CONCLUSION

This paper proposess a modified K-means algorithm that utilizes both distance and SINR information to assign users to the appropriate clusters in mmWave-NOMA systems. The modified algorithm employs the Bayesian Information Criterion (BIC) to determine the optimal number of clusters, thereby enhancing the clustering performance.

The experimental results demonstrate that the modified K-means algorithm outperforms the traditional version by achieving an overall sum rate of 3 bps/Hz with 50 users and 2.6 bps/Hz with 500 users, at a transmission power of 30 dBm.

For future work, we intend to propose a modified version of the agglomerative hierarchical clustering algorithm that follows the same distance-and-SINR-based mechanism. A comparative analysis between the modified K-means and the modified hierarchical clustering algorithm will be conducted to identify the best performing approach.

REFERENCES

[1] S. Al-Sarawi, M. Anbar, R. Abdullah, and A. B. Al Hawari, "Internet of things market analysis forecasts, 2020–2030," in Proc. World Conf. Smart Trends Syst., Secur. Sustain. (WS4), 2020, doi: 10.1109/WorldS450073.2020.9210375.

[2] Cisco and S. Jose, "Cisco visual networking index (VNI) global mobile data traffic forecast update, 2017–2022 white paper," Cisco, USA, 2019.

[3] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," IEEE Netw., 2020, doi: 10.1109/MNET.001.1900287.

[4] H. T. Hoang, Q. V. Pham, and W. J. Hwang, "Spatial-temporal-DBSCAN-based user clustering and power allocation for sum rate maximization in millimeter-wave NOMA systems," Symmetry, vol. 12, no. 11, p. 1854, 2020, doi: 10.3390/sym12111854.

[5] K. T. Chui, M. D. Lytras, and A. Visvizi, "Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption," Energies, vol. 11, no. 11, p. 2869, 2018, doi: 10.3390/en11112869.

[6] Z. Ding, P. Fan, and H. V. Poor, "Random beamforming in millimeter-wave NOMA networks," IEEE Access, 2017, doi: 10.1109/ACCESS.2017.2673248.

[7] J. Choi, "NOMA: Principles and recent results," in Proc. Int. Symp. Wireless Commun. Syst., 2017, doi: 10.1109/ISWCS.2017.8108138.

[8] O. Maraqa, A. S. Rajasekaran, S. Al-Ahmadi, H. Yanikomeroglu, and S. M. Sait, "A survey of rate-optimal power domain NOMA with enabling technologies of future wireless networks," IEEE Commun. Surveys Tuts., 2020, doi: 10.1109/COMST.2020.3013514.

[9] T. P. Huynh, P. N. Son, and M. Voznak, "Secrecy performance of underlay cooperative cognitive network using non-orthogonal multiple access with opportunistic relay selection," Symmetry, vol. 11, no. 3, p. 385, 2019, doi: 10.3390/sym11030385.

[10] J. Kim, J. Koh, J. Kang, K. Lee, and J. Kang, "Design of user clustering and precoding for downlink non-orthogonal multiple access (NOMA)," in Proc. IEEE Mil. Commun. Conf. (MILCOM), 2015, doi: 10.1109/MILCOM.2015.7357604.

[11] M. S. Ali, H. Tabassum, and E. Hossain, "Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems," IEEE Access, 2016, doi: 10.1109/ACCESS.2016.2604821.

[12] E. Bellodi, R. Zese, F. Riguzzi, and E. Lamma, "Introduction to machine learning," in Mach. Learn. Non-volatile Memories, 2022, doi: 10.1007/978-3-031-03841-9_1.

[13] B. Di, L. Song, and Y. Li, "Sub-channel assignment, power allocation, and user scheduling for non-orthogonal multiple access networks," IEEE Trans. Wireless Commun., 2016, doi: 10.1109/TWC.2016.2606100.

[14] S. M. Hamedoon, J. N. Chattha, and M. Bilal, "Towards intelligent user clustering techniques for non-orthogonal multiple access: a survey," EURASIP J. Wireless Commun. Netw., 2024, doi: 10.1186/s13638-024-02333-z.

[15] J. Cui, Z. Ding, P. Fan, and N. Al-Dhahir, "Unsupervised machine learning-based user clustering in millimeter-wave-NOMA systems," IEEE Trans. Wireless Commun., 2018, doi: 10.1109/TWC.2018.2867180.

[16] A. S. Rajasekaran and H. Yanikomeroglu, "Neural network aided user clustering in mmWave-NOMA systems with user decoding capability constraints," IEEE Access, 2023, doi: 10.1109/ACCESS.2023.3274556.

[17] M. Elsayed and M. Erol-Kantarci, "Radio resource and beam management in 5G mmWave using clustering and deep reinforcement learning," in Proc. IEEE Global Commun. Conf. (GLOBECOM), 2020, doi: 10.1109/GLOBECOM42002.2020.9322401.

[18] M. Shahjalal, M. F. Ahmed, M. M. Alam, M. H. Rahman, and Y. M. Jang, "Fuzzy C-means clustering-based mMIMO-NOMA downlink communication for 6G ultra-massive interconnectivity," in Proc. 3rd Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC), 2021, doi: 10.1109/ICAIIC51459.2021.9415222.

[19] D. Marasinghe, N. Jayaweera, N. Rajatheva, and M. Latva-Aho, "Hierarchical user clustering for mmWave-NOMA systems," in Proc. 2nd 6G Wireless Summit, 2020, doi: 10.1109/6GSUMMIT49458.2020.9083909.

[20] J. Ren, Z. Wang, M. Xu, F. Fang, and Z. Ding, "An EM-based user clustering method in non-orthogonal multiple access," IEEE Trans. Commun., 2019, doi: 10.1109/TCOMM.2019.2945334.

[21] M. Shahjalal, M. H. Rahman, M. O. Ali, B. D. Chung, and Y. M. Jang, "User clustering techniques for massive MIMO-NOMA enabled mmWave/THz communications in 6G," in Proc. Int. Conf. Ubiquitous Future Netw. (ICUFN), 2021, doi: 10.1109/ICUFN49451.2021.9528659.

[22] A. S. Rajasekaran, O. Maraqa, H. U. Sokun, H. Yanikomeroglu, and S. Al-Ahmadi, "User clustering in mmWave-NOMA systems with user decoding capability constraints for B5G networks," IEEE Access, 2020, doi: 10.1109/ACCESS.2020.3039276.

[23] Rajasekaran, NOMA Integrated with Enabling Technologies and Practical Challenges, Carleton Univ., 2023.

[24] H. Sokun, A. S. Rajasekaran, O. Maraqa, H. Yanikomeroglu, and A.-A. Saad, "Deep learning-based user clustering in millimeter wave non-orthogonal multiple access communications," Google Patents, 2024.

[25] A. Alkhateeb, G. Leus, and R. W. Heath, "Limited feedback hybrid precoding for multi-user millimeter wave systems," IEEE Trans. Wireless Commun., 2015, doi: 10.1109/TWC.2015.2455980.

[26] O. El Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, "Spatially sparse precoding in millimeter wave MIMO systems," IEEE Trans. Wireless Commun., 2014, doi: 10.1109/TWC.2014.011714.130846.

[27] G. Lee, Y. Sung, and J. Seo, "Randomly-directional beamforming in millimeter-wave multiuser MISO downlink," IEEE Trans. Wireless Commun., 2016, doi: 10.1109/TWC.2015.2483493.

[28] T. S. Rappaport, E. Ben-Dor, J. N. Murdock, and Y. Qiao, "38 GHz and 60 GHz angle-dependent propagation for cellular and peer-to-peer wireless communications," in Proc. IEEE Int. Conf. Commun. (ICC), 2012, doi: 10.1109/ICC.2012.6363891.