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# Towards intelligent user clustering techniques for non-orthogonal multiple access: a survey

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**Abstract**

With the increasing user density of wireless networks, various user partitioning techniques or algorithms segregate users into smaller, more manageable clusters. The benefit of user clustering techniques in non-orthogonal multiple access (NOMA) is to optimize resource allocation and improve network performance, spectral efficiency, and user fairness in next-generation wireless networks, particularly in scenarios with a high density of users and diverse channel conditions. With increasing users, the network creates clusters before implementing non-orthogonal multiple access within these clusters. In this paper, we have organized and classified various user clustering techniques deployed from the perspective of NOMA-based communication in the current era. Furthermore, researchers have highlighted some works deploying joint resource allocation and clustering optimization based on various criteria to enhance the overall sum rate of the network. We also identify low-complexity user clustering techniques for multiple applications, e.g. the Internet of Things, unmanned aerial vehicles, and reconfigurable intelligent surfaces in the 5G and beyond communication networks.

**Keywords:** Non-orthogonal multiple access (NOMA), Fifth generation (5G), Internet of things (IoT), Reconfigurable intelligent surfaces (RISs), Spectral efficiency (SE), User clustering (UC), Unmanned aerial vehicle (UAV)

## 1 Introduction

Next-generation wireless networks foresee a massive increase in the number of devices serviced by a single base station. These devices demand seamless connectivity with exponential traffic needs. Next-generation networks are shaping towards highly dense networks in terms of users and traffic-intensive networks. By 2025, it is estimated that the number of IoT devices alone will reach approximately 27 billion [1]. Partitioning the network into smaller clusters can address such unprecedented traffic demands. Depending on the user information and network requirements, several clustering algorithms or techniques are available. An inherited trade-off always exists with all the various types of user clustering. On one hand, a random user clustering technique is likely to yield a sub-optimal solution. Conversely, an exhaustive search technique, especially for a medium-to-large number of users, comes at the cost of high computation complexity. Hence, observing how a clustering algorithm scales with increasing users and measuring the improvement achieved in the overall sum rate is attractive [2]. Non-orthogonal multiple-access (NOMA) is an enabling technology that considerably improves spectral efficiency (SE) and user fairness [3]. In NOMA, multiple users send or receive messages simultaneously/frequency/code domain by employing distinct code (code-domain NOMA) or power (power-domain NOMA) [2–4]. Moreover, the user with a better channel condition eliminates the interference of the other user with a weak channel condition by employing the successive interference cancellation (SIC) technique. User fairness in NOMA systems is improved by handling numerous users in the same resource block. NOMA schemes allow users more flexibility in scheduling their transmissions [5]. Similarly, due to its promising performance, Power-Domain NOMA (PD-NOMA) is being investigated as a possible multiple-access technique in several standardization processes and research work [4].

NOMA has been adapted to achieve higher throughput even with limited spectrum utilization. As mentioned previously, in PD-NOMA, multiple users simultaneously share the same frequency and resource block to improve spectral efficiency [4]. The recent PD-NOMA scheme is being merged with various user clustering techniques to fulfil the targeted performance of future wireless networks to form a more practical and advanced system model [5]. An optimal clustering of users is an exhaustive search that becomes increasingly intractable as the number of users increases [2].

In two-user PD-NOMA, as shown in Fig. 1, a user who is closer to the base station is considered a strong user due to its high channel gain, and a user who is far away from the base station is regarded as a weak user due to its low channel gain. Both weak and powerful user signals are superimposed on the transmitter side using different power coefficients. Due to its path loss, more power is allocated to the weak user than the strong user, as shown in Fig. 1. The weak user's signal has a high signal-to-noise ratio (SNR) at the stronger user's receiver. This implies that the strong user can successfully decode the weak user's signal and subtract it from the original received message before decoding its signal transmission. This process is known as Successive Interference Cancellation (SIC). The strong user's signal is noise at the weak user's receiver since its transmission

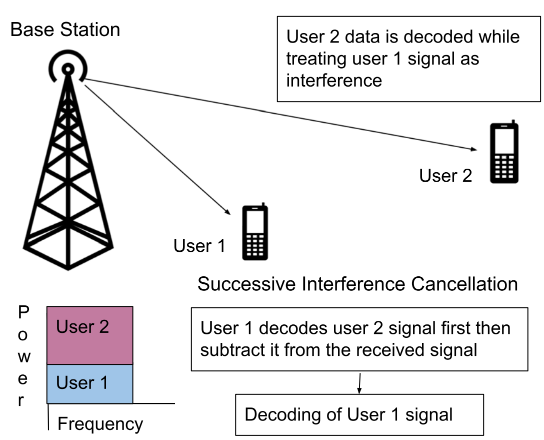


**Fig. 1** 2-user PD-NOMA

power is lower than the weak user's signal. Hence, the weak user can decode its signal without performing SIC [3]. In Fig. 1, the frequency is shared between the two users during each transmission. When the number of users increases, the frequency is shared among multiple users, which leads to interference between users and a decrease in the required sum rate. The following sections indicate that user clustering techniques can reduce complexity and optimize the network's performance.

User clustering techniques in NOMA improve the overall network performance of wireless networks. Motivated by this, a comprehensive overview of user clustering techniques within the NOMA framework, as documented in the existing literature, is presented in this paper. We discuss the user clustering techniques based on machine learning (ML) and non-machine learning (ML) approaches, specifically focusing on their applications in 5G, IoT, RIS, and UAV contexts. We highlighted the works where researchers propose low-complexity methods to handle the user clustering problem. This work also highlights the significance of user clustering schemes in enhancing PD-NOMA's downlink sum rate performance.

Based on the above observation, our main contributions are as follows.

- We present non-ML- and ML-based user clustering and their use to solve the clustering problem to optimize the performance of NOMA-based networks.
- We discuss the simulation comparison of selected user clustering methods from non-ML and ML to observe the significant impact of network performance in terms of sum rate and energy efficiency.
- We present the role of user clustering techniques in NOMA in various applications, including 5G, IoT, UAV, RIS and other networks.
- Lastly, we identify significant research opportunities for integrating user clustering techniques in NOMA and other emerging technologies.

As illustrated in Fig. 2, this paper is organized as follows. Section  discusses the user clustering techniques in PD-NOMA and various methods to optimize the sum rate of the network. We classify them into machine and non-machine learning-based methods. Section  presents works that highlight optimizing user clustering problems, specifically applications in 5G, the IoT, Unmanned Aerial Vehicles (UAV), and RIS. In the end section, we conclude the survey by summarizing future research challenges that motivated us to work in this area. The section's overview is shown in Fig. 2.

## 2 Methods of user clustering techniques in NOMA

In this section, we discussed the various methods of user clustering techniques used in NOMA based on targeting to efficiently utilize resources and improve the overall sum rate of the network. The user clustering techniques in NOMA are classified into two main categories.

- Non-machine learning-based user clustering
- Machine learning-based user clustering.

This paper classifies these various clustering techniques as shown in Fig. 3.

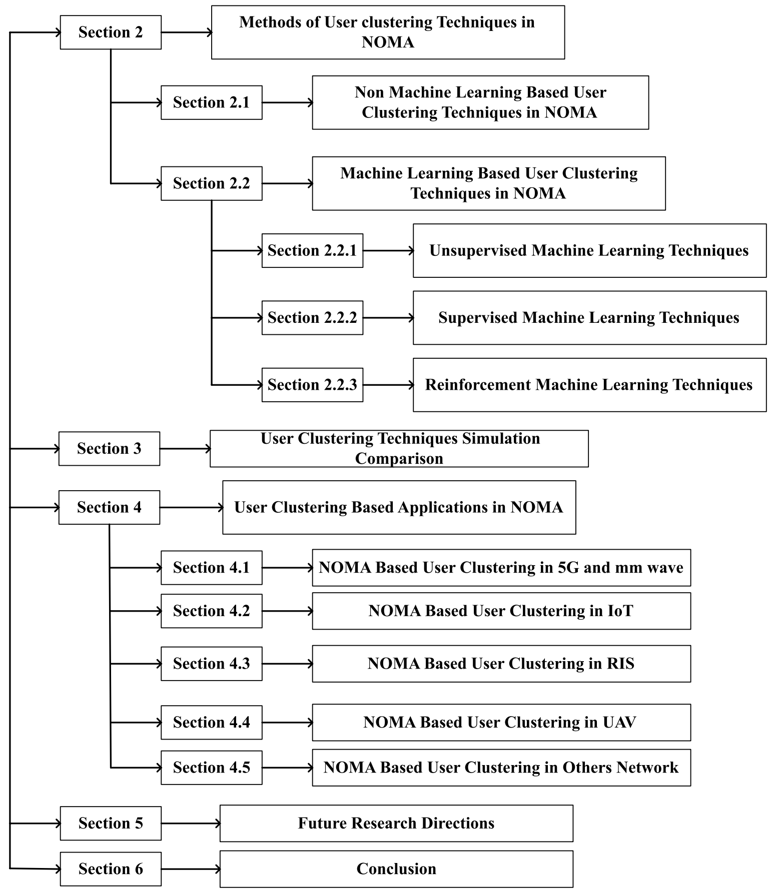


**Fig. 2** Sections overview

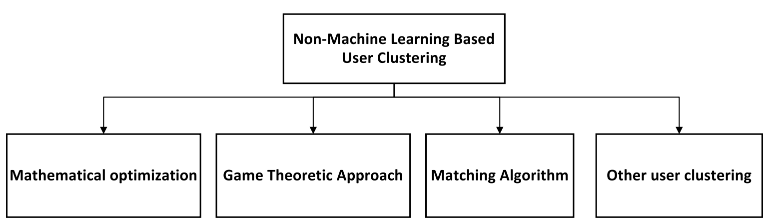


**Fig. 3** Non-machine learning-based users clustering methods in NOMA

## 2.1 Non-machine learning-based user clustering techniques in NOMA

In this section, we discussed the clustering techniques in NOMA, which are non-machine learning-based, as shown in Fig. 3. Non-machine learning-based user clustering in NOMA refers to clustering techniques that do not use machine learning algorithms, such as K-means, Gaussian mixture models (GMM), or expectation–maximization (EM). Instead, these techniques use heuristics, mathematical optimization, or other methods to group users in a NOMA system based on their channel conditions and other parameters. Non-machine learning-based clustering techniques have the advantage of being simple, fast, and easy to implement. However, they may not be as accurate or flexible as machine learning-based techniques, especially in complex and dynamic NOMA systems.

#### 2.1.1 Mathematical optimization-based user clustering

*Semi-definite programming (SDP)-based user clustering* It is an optimization problem where the variables are matrices subject to constraints that ensure they are positive and semidefinite. The clustering problem is formulated as an SDP optimization problem. This approach aims to find a matrix representing the cluster assignments, considering the power allocation and interference constraints in NOMA. The objective is to find a clustering solution that maximizes performance metrics, such as the total capacity or the maximum sum rate among all the users. In [6], the correlation clustering problem is formulated as a user clustering problem for 5G and solved using SDP. The optimal values are then approximated using Goemans–Williamson rounding, which selects different numbers of hyperplanes. In [7], the importance of semidefinite programming (SDP) for energy-efficient optimization framework designed for advanced wireless communication systems, specifically, multi-cluster simultaneous transmitting and reflecting intelligent reflecting surfaces (STAR-IRS) of the future sixth-generation (6G) wireless communication.

*Particle swarm optimization* Particle swarm optimization (PSO) is used to find the optimal clustering solution by treating the clustering problem as an optimization problem. The objective function to be optimized could be a measure of clustering quality, such as the sum of inter-cluster distances or the difference between the intra-cluster and inter-cluster distances. Each particle in the swarm represents a possible clustering solution, and the velocity and position of each particle are updated based on the information from other particles and the best solution found so far. The algorithm continues until a satisfactory solution is found or a stopping criterion is met. In [8], joint user clustering with power allocation is proposed to reduce the energy consumption of smart mobile devices in mobile edge computing (MEC). The algorithm solves the user clustering and resource allocation problem and allocates power to each cluster according to the PSO method to improve the sum rate.

#### 2.1.2 Game-theoretic approach-based user clustering

A coalition matching approach is a game-theoretic approach where users are considered players who form coalitions to optimize their resource allocation. However, it is a complex algorithm and may be computationally expensive, especially for large-scale NOMA systems. The two-sided coalition matching approach is proposed in [9] for joint user clustering with base station selection. The closed-form solution is obtained by a unique cluster beamforming method to improve the sum rate in MIMO-NOMA.

#### 2.1.3 Matching algorithm-based user clustering

The matching algorithm can match users to clusters based on channel conditions, such as gains, path losses, or delay spreads. The algorithm uses mathematical methods to determine the best pairing between users and clusters based on criteria such as the sum rate, energy efficiency, or fairness among users. Different matching algorithms can be used for NOMA clustering, including the maximum weighted matching

(MWM) algorithm, the Hungarian algorithm, and the bipartite graph matching algorithm. A joint user clustering and power allocation for the downlink RIS-based NOMA is implemented in [10]. A matching algorithm solves the clustering problem where multiple users are served on each sub-carrier. The paper conducts energy efficiency optimization for a downlink RIS-assisted NOMA system. The user clustering, passive beamforming, and power allocation are jointly optimized to maximize the system's energy efficiency. The basic steps are mentioned in Algorithm 1.

**Algorithm 1** Matching algorithm-based users clustering

1: Calculate the similarity matrix $SM_{nxn}$
2: Calculate the partial grouping power (PGP) of each feature
3: Based on the similarity matrix, assign the objects to cluster
4: Check if any items have not yet been assigned to a cluster; if so, proceed to the next phase; otherwise, go to step 8
5: Features with the lowest PGP should be removed if there are numerous features.
6: Update the similarity matrix
7: Go to step 3
8: **END**

#### *2.1.4 Other user clustering algorithm*

Another work based on joint user clustering and power allocation using an iterative algorithm is proposed in [11]. Authors claim to reduce the total power consumption needed for decoding the users. Authors can transform the original problem with nonlinear rate constraints into a linear rate constraints problem. Authors adopt the penalty and compressive sensing methods to solve a sequence of tractable convex problems. In [12], a two-layer user clustering algorithm is suggested to improve the power efficiency that successively chooses each cluster's head and tail users. The user clustering technique in [13] forms users into groups, and then iterative power allocation is used to maximize the spectral efficiency of beamspace MIMO-NOMA. In [14], a novel user clustering in beamspace MIMO is presented to improve the system performance using dynamic power allocation. The users are assigned randomly to clusters, and RF chains are allocated to each group. The proposed scheme enhances spectral efficiency compared to the other techniques. The user clustering is per- formed for multi-user scenarios based on the user's location, which is known by the base station in [15]. The proposed clustering scheme, along with power allocation, significantly improves the sum rate of the beamforming multi-user network. The clustering technique uses maximum weight matching repeatedly to create clusters for each resource block [16]. In multi-carrier uplink NOMA, we address the problem of grouping users into clusters of arbitrary size and allocation. In [17], the adaptive user clustering (AUC) scheme is proposed by using the brute force search method (B-FS), in which the best partition is selected by searching all the possible partitions with the highest throughput. The clusters of users are divided into adaptive clusters based on the degree of granularity that hierarchical clustering can handle. In [16], a user clustering algorithm is proposed along with joint power allocation and beamforming in MISO-NOMA downlink. Multiple clusters of two users are created, with one transmission beam in each group.

### 2.2 Machine learning-based user clustering

Machine learning-based user clustering in NOMA groups users into similar clusters using machine learning algorithms based on their characteristics and behaviours. Some commonly used algorithms for user clustering include K-means, hierarchical clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The choice of algorithm depends on the specific requirements and nature of the data. Figure 4 shows the classification methods of user clustering techniques based on machine learning. Machine learning-based clustering algorithms can be divided into three categories:

- Unsupervised machine learning-based user clustering methods
- Supervised machine learning-based user clustering methods.
- Reinforcement machine learning-based user clustering methods.

This section has discussed the different classes of machine learning used for user clustering in the literature.

#### *2.2.1 Unsupervised machine learning techniques*

We start by listing the unsupervised techniques for clustering. It is a technique in which classification models are trained without being supervised using an unlabelled dataset. The purpose of unsupervised learning is to discover the underlying structure of the dataset and group the users according to their similarities. Unsupervised learning is beneficial for extracting relevant information from unlabelled data.

*Hierarchical users clustering* Within unsupervised clustering methods, we start by discussing hierarchical user clustering. The clusters are created using a tree-like structure known as a dendrogram. The dendrogram's root node represents the entire data collection, whereas each leaf node represents a data object. The distance between each pair of objects or clusters, or between an object and a cluster, is commonly expressed by the height of the dendrogram. There are two types of hierarchical clustering methods: (1) the agglomerative method and (2) the divisive method. These methods denote the granularity degree that hierarchical clustering is capable of handling.

1. Agglomerative Clustering

   Agglomerative clustering constructs clusters iteratively, initiating with one cluster and progressively assimilating it into similar clusters. In this method, the clustering starts with one object inside a cluster, and after that, a series of merge procedures are performed, resulting in all objects being assigned to the same group [22]. It is also called the bottom-up approach. Algorithm 2 mentions the basic steps of agglomerative clustering.

**Algorithm 2** Agglomerative user clustering

1: Each data point is given to a single cluster.
2: After calculating the Euclidean distance measurement, calculate the distance matrix.
3: To merge the clusters, determine the linkage criteria.
4: Update the distance matrix
5: Repeat Step 1 to Step 4 until all the data points have merged into a single cluster.
6: **END**

2. Divisive Clustering

Divisive clustering begins with a single cluster and divides or splits the cluster into suitable child clusters iteratively. The entire data set belongs to a cluster, and a technique divides it into singleton clusters one by one [22]. It is also called the top-down approach. Algorithm 3 shows the basic steps of divisive clustering.

**Algorithm 3** Divisive user clustering

1: Initially, the entire dataset was assigned to a single cluster.
2: Calculate the distance matrix after determining the Euclidean distance measurement
3: To partition the least similar cluster by using linkage criteria.
4: Update the distance matrix
5: Repeat Step 1 to Step 4 until you reach the desired number of clusters.
6: **END**

In [23], the agglomerative hierarchical clustering technique is used for user distribution inside the cell. The main advantage of this technique is that it is not mandatory to specify the number of clusters before clustering compared to other clustering methods. The distribution of users inside the cell is random, which makes it very difficult to predict the cluster before applying the clustering method. The clustering method used in [23] is hierarchical clustering, which automatically determines the ideal number of clusters. In the end, the author in [23] compares the hierarchical clustering method with the K-means clustering method, and their result proves that the hierarchical method performs better to maximize the sum rate in NOMA.

*Expectation–maximization-based algorithm*

This method estimates the maximum likelihood in the presence of latent variables. It does so by estimating the latent variable values, optimizing the model, and then repeating these two steps until convergence is achieved. In [24], the EM-based algorithm is used for fixed user scenarios, and the EM-based online algorithm is used for dynamic user scenarios. It is an unsupervised machine learning technique to solve the clustering problem in NOMA. The base station knows all users' channel state information within the small cell. These users are distributed using a Gaussian mixture distribution inside $k$ clusters. The EM algorithm's overall purpose is to discover the most likely solution for models with unobserved variables [25]. It is used to extract data features and divide users accordingly into separate clusters [26]. It is an iterative method that alternates between modes (E step and M step). Unlike other clustering algorithms such as K-means and closest neighbour, EM can analyse the data distribution in each cluster and discover the maximum likelihood parameters of a statistical model for the clusters [27]. The proposed EM algorithm [24] includes steps mentioned in Algorithm 4.

**Algorithm 4** Expectation–maximization-based users clustering

1: Takes the input, which includes numbering of users $U$ and clusters $K$
2: Select the initial setting of the model parameter
3: Evaluate the posterior distribution using model parameters in **E step** that estimate the dataset's missing variables.
4: The parameters are re-estimated by using the expectation of the complete data log-likelihood
5: Evaluate the log-likelihood and check for convergence
6: **END**

Online expectation–maximization is used when the channel state information of users is changed. The clusters should be updated according to the re-estimated user distribution of the clusters because the users have changed [28]. However, the user's state is constantly changing with a real-time system. The update of the new users is not timely and reduces the system's performance when the desired threshold is not met. In the E step, sufficient statistics are changed by updating the information of the arriving user at time $t+1$. The model's new parameters are then re-estimated using the revised statistics in the M-step [28].

*Density-based clustering method* Density-Based Spatial Clustering of Applications with Noise (DBSCAN) needs several settings, including the neighbourhood distance and threshold [29]. The neighbourhood distance sets the radius of the sample point, and its threshold is adjusted by changing the minimum number of sample points inside the radius of the neighbourhood range to be marked as a core point. DBSCAN builds clusters in stages, starting with a new cluster C and an unassigned core object x, then allocating all points to C that are directly or indirectly associated with x. The main DBSCAN algorithm requires two parameters, epsilon ($\epsilon$) and min-pts. $\epsilon$ represents the radius of the neighbourhoods around a data point x. If the $\epsilon$ value is too low, a significant portion of the data will be classified as outliers. If the value of $\epsilon$ is very large, the cluster will merge, and most data points will be in the same cluster. The other parameter, min-pts, represents the minimum number of data points we want in a particular point's neighbourhood to define a cluster. This algorithm has three data points: (1) core point, (2) border point, and (3) noise or outlier. The core point is a point that has a higher value of min-pts within the radius of $\epsilon$. The border point is a point that has a lower value of min-pts within the radius of $\epsilon$. Noise represents those points that are not considered core points and border points. The following pseudocode gives the main Algorithm 5 of DBSCAN. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) needs several settings, including the neighbourhood distance and threshold [29]. The neighbourhood distance sets the radius of the sample point, and its threshold is adjusted by changing the minimum number of sample points inside the radius of the neighbourhood. DBSCAN has been deployed for online user clustering and beam selection in the mm-wave NOMA network [30]. In this work, DBSCAN is used for online clustering, and a deep Q-learning method is used for resource allocation. The primary purpose of the online clustering method is to identify the optimal value of the beam for coverage, which is dynamic based on user distribution within a network. After clustering, it produces a series of beams that provide range to all network users. [30] also compares the proposed clustering method with the K-means baseline, which indicates that the proposed method performs better to maximize the throughput in mm-wave NOMA.

**Algorithm 5** DBSCAN user clustering

1: Identify the core points or those visited with more than min_pts neighbours by locating all of the neighbor points inside $\epsilon$.
2: Make a new cluster for each core point if it isn't already assigned to one.
3: Find all of its density-related points recursively and place them in the same cluster as the core point.
4: The clusters are then enlarged by recursively repeating the neighbourhood computation for each surrounding point.
5: **END**

*K-means-based user clustering* In this clustering method, partitions of objects are organized into a k cluster. This approach locates k centroids before assigning each data point to the cluster nearest to it. In the first phase, k centres are selected randomly, which is a fixed number, followed by a second phase in which clustering is carried out based on the Euclidean distance measured between users and the randomly selected cluster centres. Next, iteratively update the cluster centroids by averaging the users in each cluster and recalculating the cluster of each user using Euclidean distance. This iterative clustering process is repeated until centroids do not change [38]. In [31], authors have presented an online K-means clustering method for user clustering for the dynamic user scenario. An iterative technique is proposed in [32] to optimize the system's minimal sum rate for a UAV-based NOMA network in a limited time. Algorithm 6 shows the basic steps of K-means clustering.

**Algorithm 6** K-means user clustering

**Steps**
1: For the number of clusters, choose/input k.
2: Randomly select k points as centroids
3: Calculate the Euclidean distance between users and centroids
4: Calculate the cluster centroids by averaging all the data points corresponding to each cluster.
5: Continue iterating until the centroids do not change.
6: If there is a reassignment, go to Step 4; otherwise, go to Step 7.
7: **END**

*Enhanced K-means-based clustering* In enhanced K-means clustering, also known as K-means ++, a smart centroid initialization is done compared to K, which means clustering. K-means ++ clustering solves the problem of random picking of centroids. The algorithm of enhanced K-means is utilized in [39] for clustering. [35] presents enhanced K-means clustering to reduce interference and provide strong user correlation in clusters. The users are divided into numerous clusters using the Poisson cluster process, and each cluster is supplied by a hovering UAV equipped with NOMA [36]. The basic steps indicate Algorithm 7.

**Algorithm 7** Enhanced K-means clustering

1: To determine the range of difference between the maximum and minimum elements in the data set of each column
2: Determine which column in the data set has the largest range.
3: Sort the data set based on the largest range difference.
4: Make $K$ partitions equally based on sorted data set
5: Initialize the centroids by taking the mean value of sorted data points in step 4
6: Calculate the Euclidean distance between the centroids and all data points.
7: Calculate the cluster centroids by averaging all the data points corresponding to each cluster.
8: Continue iterating until the centroids do not change.
9: If there is a reassignment, go to Step 7; otherwise, go to Step 10
10: **END**

*K-medoids-based clustering* It is a clustering technique that divides the data set of n items into k predefined groups. Users with minimum average dissimilarity to all other objects inside a cluster are known as a medoid [40]. The method of partitioning is based on the notion of minimizing the total differences between each user. The final centroid is constructed from actual user clusters. The algorithm used in K-medoid clustering differs from the K-means clustering method, commonly known as partitioning around medoids (PAMs). Algorithm 8 of K-medoid is mentioned below.

**Algorithm 8** K-medoid clustering

1: Select clusters $K$ randomly from the users as medoid.
2: Using the distance metric approach, each user is assigned to the cluster that includes the nearest medoid.
3: In the cluster, the medoid is selected by computing the sum of the distance calculated for each user to all other users as a minimum.
4: Repeat Step 2 and Step 3 until the convergence is achieved, then go to Step 5
5: **END**

*Fuzzy C-means-based users clustering* It is an unsupervised clustering technique based on feature analysis that divides data points into clusters [34]. A fuzzy C-means method based on the channel quality of service (QoS) characteristics is presented for user clustering [33] in the MIMO system. The detail of this Algorithm 9 is presented below as mentioned in [34]

**Algorithm 9** Fuzzy C-means users clustering

1: Determined the number of clusters and fuzzy exponent
2: To establish partial participation with a cluster, each user is assigned a membership function.
3: The centroid is computed for each user repeatedly until the cost function is minimized to a certain threshold
4: **END**

This clustering method has its low inter-cluster variant property that can perform efficiently and provide faster convergence when many users (IoT devices) are connected in a MIMO-NOMA network [33].

### 2.2.2 Supervised machine learning techniques

Supervised learning is a machine learning technique that uses well-labelled training data for training before predicting the clustering based on test data. The main goal is to discover a mapping function that will map the input variable to the output variable.

*Artificial neural network-based user clustering* The artificial neural network (ANN) method is a supervised machine learning technique that can be employed for user clustering in NOMA. Initially, the ANN model is trained using a historical data set, which includes the users' channel gain and transmitting power. In the next phase, validation is performed by tuning the model's hyperparameters to evaluate cluster formation. Finally, the ANN model is tested with the learned parameters and tuned hyperparameters to predict the formation of clusters, and the model's accuracy is evaluated. The suggested technique puts users into clusters based on the trained neural network. In [41], the authors have presented an ANN-based user clustering scheme for the 5G downlink PD-NOMA network.

*Deep neural network-based user clustering* A deep neural network (DNN) is a supervised machine learning method for clustering. Authors in [42] present an implementation of DNN clustering with a feed-forward neural network to partition nodes into two disjoint clusters, maximizing the resulting ergodic sum rate. In [43], DNN is used for clustering to characterize the nonlinearity between the cluster formation with channel diversity and transmission powers in NOMA. The authors examine the mean square error of DNN and throughput performance in an asymmetrical fading NOMA channel after training it with training samples and validating it with testing data.

*Long short-term memory-based user clustering* Another supervised approach is the long short-term memory (LSTM) technique proposed in [47]. In this work, multiple LSTM layers with hidden cells are used to handle time-series input data to improve the prediction accuracy of NOMA users. The feedback connections in the LSTM layer are used to check the dependency of cluster information based on time series data in layers. The proposed technique, based on LSTM, improves the overall sum rate in NOMA.

*Extreme learning machine user clustering* An Extreme Learning Machine (ELM) is a machine learning algorithm belonging to the feed-forward neural network family. ELM has been used for various applications, including clustering. In [45], ELM solves the ANN learning speed problem by gradient-based back-propagation (BP) algorithm. The input weights and bias for the hidden layer nodes of ELM are generated randomly, and parameter adjustment is unnecessary compared to ANN. Based on the channel gains and powers of the users, it is possible to estimate the ideal cluster formation quickly by using ELM. The proposed ELM [45] is a fast learning and low-complexity algorithm used for user clustering compared to the other machine learning approaches.

*Genetic algorithm-based user clustering* Genetic algorithms (GAs) are numerical and combinatorial optimizers that can tackle problems that are not linear or convex. The user clustering optimization by using GA improves the overall sum rate of the multi-user hybrid NOMA network [46]. The limitation of the number of users inside the cluster is not applicable. This problem can be solved by using genetic Algorithm 10. In [46], a based user clustering strategy is presented, assuming that the power of users is known within each cluster. Linear programming is used to find a power allocation plan that satisfies the minimum rate restriction. The detailed steps of GA are mentioned in Algorithm 10.

**Algorithm 10** Genetic algorithm-based users clustering

1: **Population initialization** K randomly chosen locations from the data set are used to initialise the K cluster centers encoded in each chromosome. This procedure is done for each of the population's P chromosomes.
2: **Fitness computation** Clusters are established based on the centers encoded in the chromosome. The mean points of the various clusters replace the cluster centers encoded in the chromosome.
3: **Selection** The chromosomes are chosen from the mating pool during selection. A proportional selection strategy is used in various ways, including roulette wheel selection.
4: **Crossover** It is a probabilistic process in which two parent chromosomes exchange information to generate two child chromosomes.
5: **Mutation** Each chromosome has a predetermined mutation rate. A bit location (or gene) is altered in the binary form of chromosomes by simply flipping its value.
6: **Termination condition** The method stops when a maximum number of generations has been formed or the population has reached a certain fitness level.
7: **END**

### 2.2.3 Reinforcement learning techniques

It is a machine learning algorithm in which an agent learns the best actions by interacting with its surroundings. However, in the learning process, the values chosen for learning algorithm parameters can considerably impact the overall learning process. Reinforcement learning algorithms used in NOMA to solve user clustering and power allocation problems are mentioned in Fig. 4. The details of these techniques are listed below.

*State–action–reward–state–action (SARSA)-based user clustering* It is a reinforcement learning technique, a temporal difference (TD) learning algorithm. It learns from the difference between the estimated value of the current state–action pair and the estimated value of the next state–action pair. In SARSA, the agent knows a policy that maps each state–action pair to an expected cumulative reward, called the Q-value. The agent updates its estimate of the Q-value for the current state–action pair based on the reward it receives and the Q-value of the next state–action pair it chooses according to its current policy.

The SARSA algorithm uses an on-policy approach, meaning it learns the value of the policy it is currently following. This is in contrast to off-policy algorithms like Q-learning, which learn the value of the optimal policy regardless of the policy being followed.

SARSA steps are described in Algorithm 11 for user clustering problem as in [48].

**Algorithm 11** SARSA Q-learning-based users clustering

1: Initialize Q table $Q(s,a)$
2: Initialize Q learning parameters
3: Users are randomly assigned to any BSs and Clusters.
4: Calculate objective functions
5: Reward are assigned based on calculating objective functions
6: Update Q table entries
7: Return optimal clustering solution
8: **END**

*Deep reinforcement learning (DRL)-based user clustering* It is used to solve the complexity of the Q-learning method that requires high memory to build state space. This is one of the drawbacks of Q-learning in a practical system. Rather than allocating considerable memory to all possible state and action pairings, the DRL agent must know the weights. The key benefit of DNN is that it reduces Q-tables' complexity by requiring less memory. DRL agent iteratively updates based on previous states, actions, and reward values as implemented in [48].

*Modified object migration automation (MOMA)-based user clustering* This clustering technique is used for sum rate maximization of the RIS-based NOMA in [49]. In MOMA, they are grouping the number of users into equal-sized clusters. Typically, in NOMA, user clustering is one of the primary problems because a single resource block can only handle a few mobile users. The users are grouped based on their strengths to solve this issue. As a result, if two users are from the same group, we must eliminate their pairs because in NOMA, one user should be strong, and the other should be weak. User clustering is based on their placements and the channel conditions to increase user partitioning performance [49]. The main elements of the proposed clustering technique are mentioned below.

– Initialize $K$ actions
– Initialize states for each action
– Reward is awarded according to the action

*Coalition game approach-based user clustering* A coalition game examines players' cooperative actions that have been widely used to solve clustering issues [54, 55]. The goal of the coalition game is to establish a durable coalition structure based on the merge and split rule. All players in the game must follow these rules strictly and gain benefits to join the coalition. This approach provides fast coverage, especially in a distributed environment. Furthermore, if many users are examined, the coalition game permits the size of a NOMA cluster to be adjustable in the user's clustering process [50]. The network has three most used games: (1) Matching games, (2) Stackelberg games, and (3) Coalition games. In [55], a coalition game approach was proposed for implementation in wireless sensor networks. The following three points should be addressed while developing a coalition-forming algorithm [55] for a specific application) the order should be correct, 2) Rules for modifying partitioning, and 3) determining the partition's stability. The main objective of this approach is to distribute gains from the cooperation between the players fairly, but these gains are assigned at the cost of the forming coalition. A sequential game-based algorithm (SGA) is proposed for solving the user clustering game [53]. [59]. The joint user clustering with power allocation is optimized using the Stackelberg game. There are two cases to be considered to improve the sum rate of the network with different rate requirements. In this proposed algorithm, participants are rigidly ranked and strategist based on their positions. The sequence of steps mentioned in [56] for the sequential game is as follows.

- The game begins with the first participant in any given sequence.
- A proposal is submitted by the presently active player, inviting other players to join him in building a new coalition.
- The proposition must be responded to in sequence by all other players. Players can either accept the proposal and join the coalition, or they can reject it and remain in their present coalitions

This approach performs well in terms of the sum rate and outage probability [53]

## 3 User clustering techniques simulation comparison

In this section, we discussed the simulation comparison of some user clustering techniques, which are mentioned in Tables 1, 2, 3 and 4.

The simulation results of the clustering techniques, which are based on non-ML, show a significant improvement in the sum rate of the PD-NOMA scheme. [10] solves user clustering problem using a matching algorithm. This iterative algorithm is developed based on joint user clustering and beamforming in downlink PD-NOMA to optimize energy efficiency by solving these sub-problems. The simulation results in [10] represent the improvement in energy efficiency of RIS-based NOMA compared to the other techniques, including NOMA and OMA.

**Table 1** Non-machine learning-based user clustering schemes in NOMA

| Clustering scheme | Related work | Scenario | Assumptions | Objective functions | Application | Findings |
|---|---|---|---|---|---|---|
| Mathematical optimization | [6, 8, 18] | Downlink | CSI is known at base station | Sum rate maximization | MISO | (1) It performs better than random clustering (2) Jointly user clustering and power allocation |
| Game-theoretic approach | [9] | Downlink | The channels assumed to be Rician fading | Maximize the energy efficiency | MIMO | Joint user clustering, passive beamforming and power allocation |
| Matching algorithm | [10] | Downlink | The channels assumed to be Rician fading | Maximize the energy efficiency | RIS assisted NOMA | Joint user clustering, passive beamforming and power allocation |
| Other user clustering techniques | [12] | Downlink | Users inside a cell are independent of path loss effect | Sum rate maximization | MU-MIMO | To suppress multi-user and inter-symbol interference |
| | [13, 14] | Downlink | Assume no inter-cluster interference | Higher spectral efficiency | Massive MIMO | To improve performance by NOMA beamspace with efficient user clustering |
| | [15] | Downlink | Location information is assumed to be known by the UE | Sum rate maximization | 5G mm-wave | Location aided clustering approach is used for cluster assignment and improves the performance as compared to other beamforming schemes |
| | [16] | Uplink | BS knows perfectly all the channel gains | Reduce system latency | MISO | To solve the problem of user clustering by optimally resource block allocation with time-based proportional fairness |
| | [17] | Downlink | CSI is known at the base station, fixed user distances | Improves transmission power | MISO | Iterative power and joint user clustering algorithm reduces the system's power consumption |
| | [19] | Downlink | CSI is known at the base station | Sum rate maximization | SISO | This schemes used Brute Force Search method and improves system performance |

**Table 1** (continued)

| Clustering scheme | Related work | Scenario | Assumptions | Objective functions | Application | Findings |
|---|---|---|---|---|---|---|
| | [20] | Uplink | No intercell interference from other neighbouring cells | Sum rate maximization | Narrow band IoT | (1) Joint user clustering and resource allocation of MTC devices<br>(2) Satisfying the QoS requirements and transmission power in each cluster |
| | [21] | Uplink | CSI is known at the base station | Higher spectral efficiency | MISO | Provides optimal solution for decoding order and power control |
| | [11] | Downlink | CSI is known at the base station | Minimize total power consumption | SISO | (1) Consider decoding power consumption<br>(2) Compressive sensing method is used to solve the convex problem |

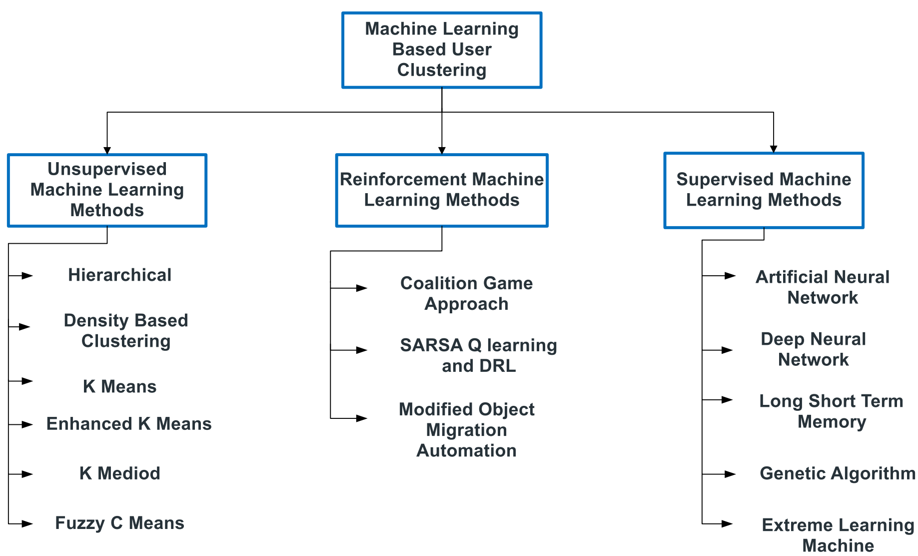


**Fig. 4** Machine learning-based user clustering methods in NOMA

Next, we compare the clustering techniques of the unsupervised ML class, including K-means, enhanced K-means, and hierarchical, by considering a network scenario in the PD-NOMA downlink, as shown in Fig. 5.

*Network Scenario* Consider a PD-NOMA downlink network in which the base station (BS) serves multiple users, i.e. $N = 12$. These users are independently identically distributed (i.i.d) inside the cell. It is assumed that the BS knows the channel state information (CSI) of all users inside the cell exactly. The channel gain is calculated according to the

**Table 2** Unsupervised machine learning-based user clustering schemes in NOMA

| Clustering scheme | Related work | Scenario | Assumptions | Objective functions | Application | Findings |
|---|---|---|---|---|---|---|
| K-means | [31, 32] | Downlink | User distribution follows the Poison Cluster Process inside cell | Sum rate maximization | mm-wave MISO, UAV | (1) Jointly user clustering, power allocation and beamforming for scheduling of UAV trajectory (2) Optimal user clustering |
| Fuzzy C-means | [33, 34] | Downlink | CSI is known by the base station | Maximize energy and power | Massive MIMO | Clustering is based on QOS requirement of user and provides fast convergence rate |
| Enhanced K-means | [35, 36] | Downlink | CSI is known by the base station | Maximize energy efficiency | Tera-Hertz MIMO, MISO UAV | (1) Cache-enabled system to handle heterogeneous environment with fast converging rate (2) Joint user clustering and beamforming for scheduling of UAV trajectory |
| Hierarchical | [37] | Downlink | User distribution follows the poison cluster process inside cell, perfect CSI is known by the base station | Sum rate maximization | mm-wave MISO | The clustering scheme provides no need to fix the number of clusters and provide more accurate result in case of random user distribution |
| DBSCAN | [30] | Downlink | User distribution follows the poison cluster process | Sum rate maximization | mm-wave MISO | The clustering scheme provides the QOS-based beamforming |

distance of users from the BS. The user closer to the BS has more stronger channel gain than the other BS users. These users are arranged in $j$ cluster using unsupervised ML-based clustering techniques.

$$\left|h_1\right|^2 > \left|h_2\right|^2 > \ldots > \left|h_{12}\right|^2 \tag{1}$$

The SIC decoding order is based on the channel gains arrangement of users in NOMA. The signal-to-interference plus noise ratio (SINR) for each user inside a cluster $j$ is expressed in Eq2.

**Table 3** Supervised machine learning-based user clustering schemes in NOMA

| Clustering scheme | Related work | Scenario | Assumptions | Objective functions | Application | Findings |
|---|---|---|---|---|---|---|
| Artificial neural network (ANN) | [41] | Downlink | Base station knows the CSI of all the users | Sum rate maximization | 5G | Predict the cluster formation automatically to reduce the computational complexity. |
| Deep neural network (DNN) | [42] | Uplink | Base station knows the CSI of all the users | Sum rate maximization | MIMO | Cluster formation based on feed-forward neural network. |
| | [43] | Downlink | Base station knows the CSI of all the users | Sum rate maximization | MISO | It is suitable for clustering more complex scenario and enhance computational complexity. |
| Long short term memory (LSTM) | [44] | Downlink | Base station knows the CSI of all the users | Sum rate maximization | 5G | Clustering is based on time series data which effectively predicts the number of cluster as compare to exhaustive search method. |
| Extreme learning machine (ELM) | [45] | Downlink | Base station knows the CSI of all the users | Throughput maximization | 5G | Optimized clustering based on fast learning speed of ELM at low complexity. |
| Genetic Algorithm | [46] | Downlink | Base station knows the CSI of all the users | Throughput maximization | MISO | Reduces the complexity of clustering as compared to the other exhaustive search method. |

$$\gamma_i^j = \frac{P_i^j \beta_i^j \left|h_i^j\right|^2}{\sum_{k=1}^{i-1} P_i^j \beta_i^j \left|h_i^j\right|^2 + \sigma_n^2} \forall i \in N \tag{2}$$

$P_i^j$ represents the power and $\left|h_i^j\right|^2$ represents the channel gain of the user $\forall i \in N$ for cluster $j$. Where $\beta_i^j$ represents the power allocation factor, which summation usually is equal to 1 for the number of users inside a cluster $j$, the achievable throughput $R_i^j$ for the $i$-th user assigned to the $j$-th cluster is expressed in Eq 3.

$$R_i^j = \sum_{i=1}^{N} \mathrm{B} \log_2 \left(1 + \gamma_i^j\right) \tag{3}$$

We obtained the clustering results by employing clustering algorithms, as illustrated in Table 5. These clustering techniques (K-means, enhanced K-means, and hierarchical) produce different numbers of clusters $j$ for a given network scenario according to their algorithms, which we have already discussed in 3, 8 and 9. The K-means cluster

**Table 4** Reinforcement machine learning-based user clustering schemes in NOMA

| Clustering scheme | Related work | Scenario | Assumptions | Objective functions | Application | Findings |
|---|---|---|---|---|---|---|
| SARSA Q-learning deep reinforcement learning | [48] | Uplink | Base station and users equipped with omnidirectional antennas | Sum rate maximization | IoT | To solve user clustering problem in light and heavy traffic |
| Modified object migration automation algorithm | [49] | Downlink | Base station knows the CSI of all the users | Sum rate maximization | RIS | To make clusters are in equal size and perform long term resource allocation |
| Coalition game approach | [50] | Downlink | Base station knows the CSI of all the users | Spectral efficiency maximization | 5G MIMO | Improved cluster beamforming approach due to its fast convergence and flexible cluster size |
| | [51] | Downlink | Base station knows the CSI of all the users | Sum rate maximization | Hybrid MISO | Clustering is performed by obtaining the optimal solution |
| | [52] | Downlink | Sub carrier assignment must before the resource allocation of users.<br>Base station knows the CSI of all the users | Throughput maximization | Device to device | Clustering is based on the basis of coalition and their maximum utility |
| | [53] | Downlink | Number of clusters must be equal to the RF sources in base station channel conditions known by the base station | Sum rate maximization | mm-wave MISO | Provide low-complexity user clustering mechanism for considering two different cases |

technique produces 4 clusters, and the enhanced K-means clustering technique produces 5 clusters due to the optimized selection of the initial selection of centroids. The hierarchical clustering method produces 2 clusters by using 3. These $j$ clusters consist of different numbers of users. The achievable sum rate of the cluster $j$ is calculated using Eq. 3. We performed a simulation according to the simulation parameters mentioned in Table 5. We analysed the result in terms of the sum rate of the network as shown in Fig. 5.

Figure 5 shows the sum rate performance of the network for a given transmission power of the BS. The sum rate of the network demonstrates varying improvements relative to the choice of user clustering techniques as the transmission power increases from 0 to 40 dB. We observe that the enhanced K-means clustering technique significantly improves the sum rate of the web compared to the other clustering techniques.

**Table 5** Simulation parameters

| Parameter | Value |
|---|---|
| Number of users (N) | 12 |
| Path loss exponent | 5 |
| Bandwidth | 10^6 |
| Noise power | −174 dBm |
| BS transmission power | 0–40 dB |
| K-means clusters (j) | 4 |
| Enhanced K-means clusters (j) | 5 |
| Hierarchical clusters (j) | 2 |

The comparison of supervised machine learning-based user clustering techniques, including ANN and DNN, is mentioned in [43] as shown in Fig. 6. The simulation results mentioned are based on the simulation parameters chosen in [43]. We observed that DNN performs well compared to ANN in terms of throughput (Mbps) when the number of users increases. These results are compared with the benchmark of the brute force search (B-FS) method, as shown in Fig. 6. These supervised machine learning-based techniques reduce the complexity of the clustering as compared to the B-FS method.

The different reinforcement learning techniques used to address the user clustering problem are mentioned in Table 4. A sequential game-based algorithm (SGA) is introduced to address the user clustering game (N, U). In this algorithm, players follow a strict order and determine their strategies based on the given sequence [53]. The simulation results in [53] show that the proposed algorithm significantly improves the sum rate of the mm-Wave-NOMA compared to the mm-Wave-OMA scheme.

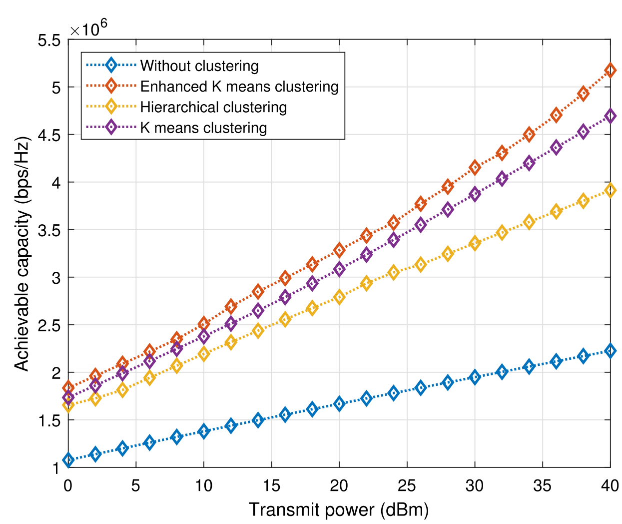


**Fig. 5** Unsupervised ML clustering techniques comparison

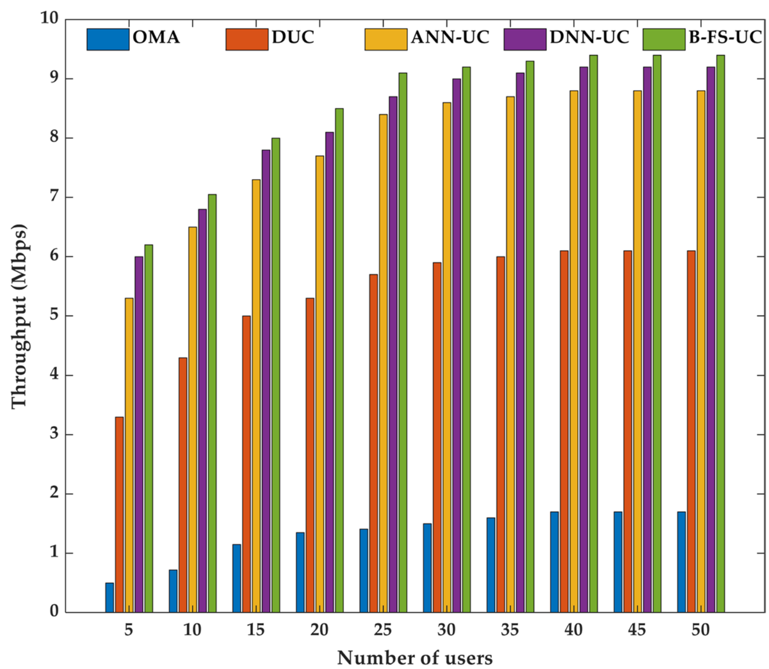


**Fig. 6** Supervised ML clustering techniques comparison [43]

## 4 User clustering-based applications in NOMA

In this section, we discuss the application of user clustering methods to address the challenges in NOMA for IoT, MIMO/MISO, 5G, UAV, RIS, and other networks. This section covers recent research related to user clustering techniques in NOMA-based applications.

### 4.1 NOMA-based user clustering in 5G and mm-wave

Some challenges in 5G and mm-wave applications are channel variations, QoS requirements, user mobility, network heterogeneity, and energy efficiency. The channel conditions can vary over time among users. The number of users inside a cell requires different QoS requirements. So, adaptive user clustering is needed to address these challenges and improve the energy efficiency of the network.

The spectral efficiency can be improved using NOMA of fifth-generation (5G) wireless networks. The author in [57] proposes a packet-level scheduling approach for the base station to identify whether to employ NOMA or OMA, pair users and allocate power. The packet-level simulations show that the suggested technique achieves a greater throughput. In [58], the author proposed a power allocation system based on reinforcement learning with a simple and efficient user clustering approach. This technique helps allocate power more efficiently to improve the sum rate. The proposed user clustering approach supports the Q-learning algorithm reaching maximum throughput in downlink and uplink NOMA systems. By relaxing the clustering variables, the user clustering problem is addressed in [6] through semidefinite programming (SDP). The optimal values are approximated using Goemans–Williamson rounding, which selects a different number of hyperplanes. The proposed clustering algorithm performs better than

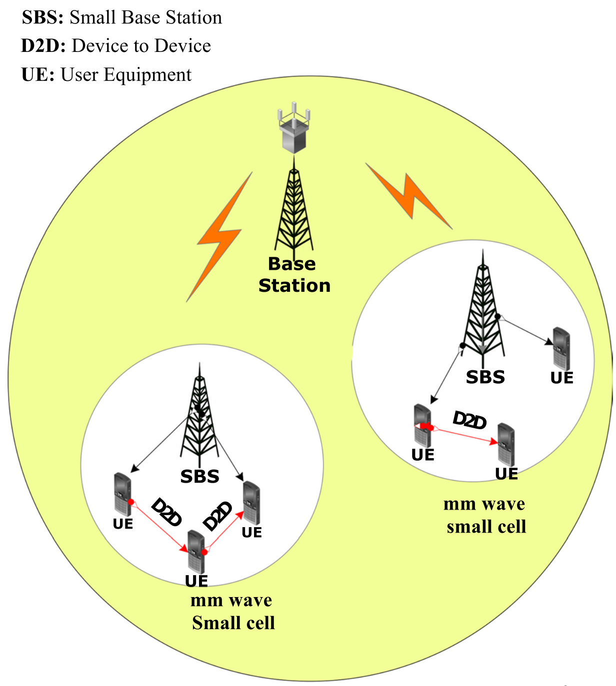


**Fig. 7** NOMA in mm-wave and 5G scenario

random users clustering. Another machine learning approach expectation–maximization (EM)-based algorithm is proposed in [28]. This approach is used to handle the problem of user clustering in both fixed and dynamic user scenarios. They use unsupervised learning to discover users' intrinsic structures and correlations and reduce computational complexity. The authors in [31] proposed an unsupervised machine learning technique, which is K-means for solving user clustering problems and improving the sum rate of the network. They also proposed an online K-means algorithm for the dynamic scenario where new users arrive regularly. Ultimately, they compare these algorithms and conclude that the online K-means user clustering performs better than traditional user clustering schemes in a dynamic scenario. The typical mm-wave scenario in 5G is shown in Fig. 7.

The appropriate number of clusters is automatically identified using the hierarchical clustering proposed in [23]. This clustering technique is used to satisfy the quality of service demands for all the users inside each cluster as compared to the K-means algorithm. The sequential game-based algorithm is proposed in [53], which increases the overall sum rate in NOMA. The hybrid precoding techniques are used at the base station by utilizing the channel state information of cluster heads (CHs). The proposed approach is used to efficiently increase the rates of cluster heads and individual members inside each cluster. The use of game theory to dynamically assign users to different clusters is allocated. In [15], authors propose a location-assisted user clustering technique in a multi-user environment for non-orthogonal multiple access. Firstly, user clustering is performed based on the user's location by the base station, and then, power allocation is performed using the Lagrange approach. The proposed technique helps improve the overall sum rate of the network compared to

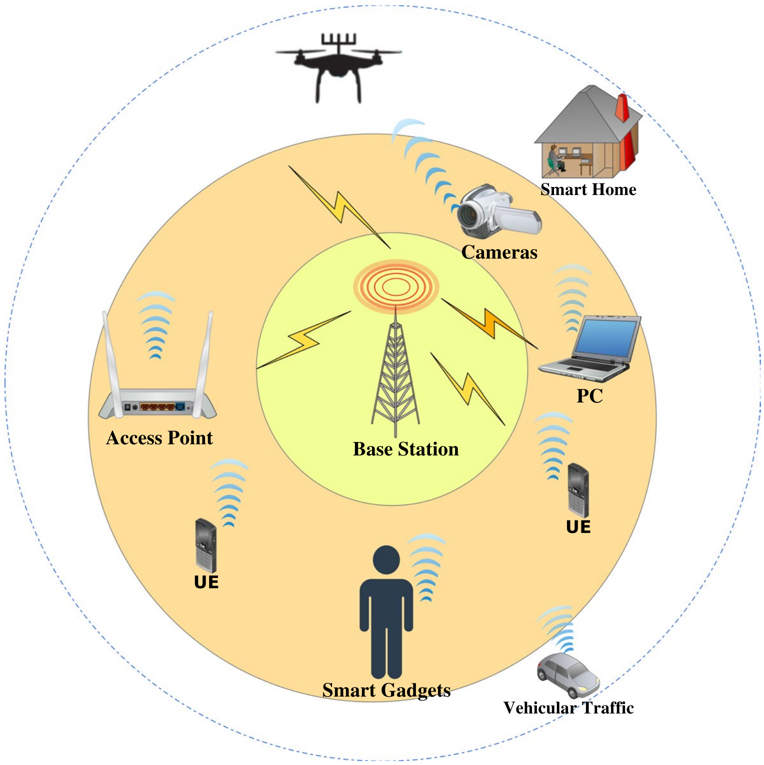


**Fig. 8** NOMA in IoT scenario

the conventional beamforming multi-user system. The unsupervised learning method using the EM algorithm is introduced in [24]. The proposed technique performs well in a fixed and dynamic scenario regarding sum rate and quickly updates the user distribution parameters with low complexity.

Clustering is required to determine the number and direction of beams in millimetre-wave (mm-wave) networks to cover users optimally. The requirement for an online clustering strategy to maintain up-to-date beams towards the mobility of users drives such clusters. In [30], the author proposed a technique for users' Ultra-Reliable Low-Latency Communication (URLLC) and enhanced Mobile BroadBand (eMBB) to optimize the quality of service-based clustering and resource allocation in a 5G network. The proposed scheme is based on DBSCAN, which clusters users online and selects the number of beams to be used. The proposed technique performs well in terms of latency compared to other techniques: K-means and priority-based proportional fairness.

### 4.2 NOMA-based user clustering in IoT

NOMA has recently been proposed to improve spectrum efficiency in mm-wave large MIMO systems. The massive connectivity and low latency are two significant problems for the IoT to meet the high standards of service demanded by the many devices. There are different quality service demands for machine-type communication (MTC) devices. The main challenge in an IoT network is to optimize the service requirement for all devices in the network. Figure 8 shows the typical IoT network scenario. The author in [59] proposed dynamic clustering for IoT devices to reduce the overall system complexity. Power allocation-based energy management ensures fairness among IoT devices using a Nash bargaining solution in each cluster. The proposed technique improves IoT device's energy efficiency and fairness compared to other techniques.

In [60], the author proposed a scheme to optimize power allocation by using an iterative algorithm. The optimal solution is achieved by updating the auxiliary variables and weight factor. The NOMA cluster assigns different ratings to machine-type communication (MTC) devices based on the quality of service (QoS) needs. A user clustering approach is proposed in [48] based on SARSA Q-learning and deep reinforcement learning to allocate resources in a multicell uplink IoT NOMA system. It divides users into groups depending on network traffic to maximize the available resources. It divides users into groups depending on network traffic to maximize the available resources. It divides the network traffic into two parts: light and heavy; for light traffic, it utilizes the Q learning method, and for heavy traffic, it uses the DRL method. The achieved capacity for all users is utilized to define the reward function to characterize the performance. The author proposed the user clustering and power allocation techniques in [61] for coordinated multi-point (CoMP) transmission in green NOMA networks. Non-orthogonal sharing causes interference in access point (AP) clusters, which increases transmit-power usage even more. The proposed technique solved this problem by efficiently combining AP clustering and power control optimization.

### 4.3 NOMA-based user clustering in RIS

The RIS (reconfigurable intelligent surface) is a new technology for more energy-efficient wireless communication. The decoding order of users in conventional NOMA networks via successive interference cancellation (SIC) is usually determined by intrinsic channel conditions that are impacted by external factors. Reconfigurable intelligent surfaces (RISs) are a channel-variation approach that can change the channel quality for specific users by varying the RIS deployment sites and reflection coefficients [62]. The significant challenges in RIS-based NOMA are channel variations, interference management, limited number of RIS elements, QoS requirements, etc. Here, an adaptive user clustering technique allocates resources efficiently without interference. This technique can transform the highly unpredictable wireless environment into a programmable and somewhat deterministic space [10]. The beamforming method in RIS-assisted NOMA networks still has to be investigated further, especially in complex and dynamic network environments.

Using RIS for intelligent communication aims to improve access point service for line-of-sight and non-line-of-sight users [63]. The author in [49] proposed combining NOMA user segmentation and RIS phase shifting to maximize the sum data rate of mobile users (MUs) in NOMA downlink networks. In [49], a MOMA technique is introduced, dividing users into clusters of equal size. The proposed RIS-assisted NOMA downlink paradigm outperforms the traditional OMA framework regarding sum data rate. In [10], the author proposed a joint user clustering with beamforming and power allocation for RIS-based NOMA to improve the sum rate of the overall network. The matching algorithm is utilized to solve the user clustering problem, and the power allocation sub-problem is handled using the difference between two convex functions (DC)

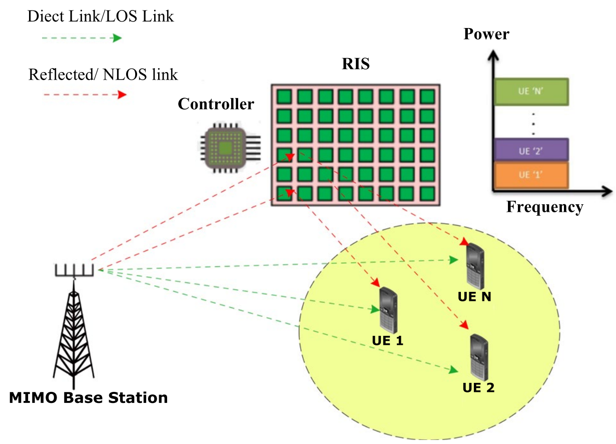


**Fig. 9** NOMA in RIS scenario

programming. The simulation results suggested that the proposed technique, which is RIS-based NOMA, performs well in terms of sum rate as compared to the traditional OMA without RIS.

The RIS network scenario applying the NOMA principle is shown in Fig. 9. The integration of RIS introduces the complexity in beamformer-based multiple-antenna NOMA due to the complexity arises because the channel quality of users is influenced by both direct links and RIS-assisted links as shown in Fig. 9. A small-scale RIS-assisted transmission scenario is considered, where a single BS serves multiple users with the help of a single RIS, as shown in Fig. 9. The RIS is assumed to be placed close to the users inside a cell. In two-user set-ups, the strong and weak User is represented as $UE_1$ and $UE_2$ as shown in Fig. 9. The passive beamformer arrangement at the RIS determines the equivalent reconfigurable channels. The User $UE_1$ directly decodes its signal received through the equal reconfigurable channel by treating the signal of User $UE_2$ as interference.

RIS deployment in NOMA systems improves spectral efficiency, reduces interference, and improves signal strength. It's important to note that RIS could be deployed to successfully adjust signal propagation throughout the network considerably more extensively due to its low cost. Commonly, RIS is deployed where there is LoS to the access point (AP) that significantly increases the information rate for users [64]. The challenges of RIS in NOMA systems are the complexity of deployment, sensitivity to channel conditions, restricted coverage, backhaul overhead, and implementation costs.

### 4.4 NOMA-based user clustering in UAV

UAV-aided wireless communications have gained a lot of interest in the research community because of their advantages in providing real-time and high throughput services [65]. The issues addressed by user clustering techniques are mobility and location management for UAVs, channel variations, QoS requirements, and optimizing resources efficiently to improve the energy efficiency of the network. The deployment infrastructure is very flexible as compared to conventional wireless communication. One of the most essential issues in NOMA is user clustering, also known as user grouping/pairing. The users are distributed in the cluster by using the Poisson Cluster Process and served

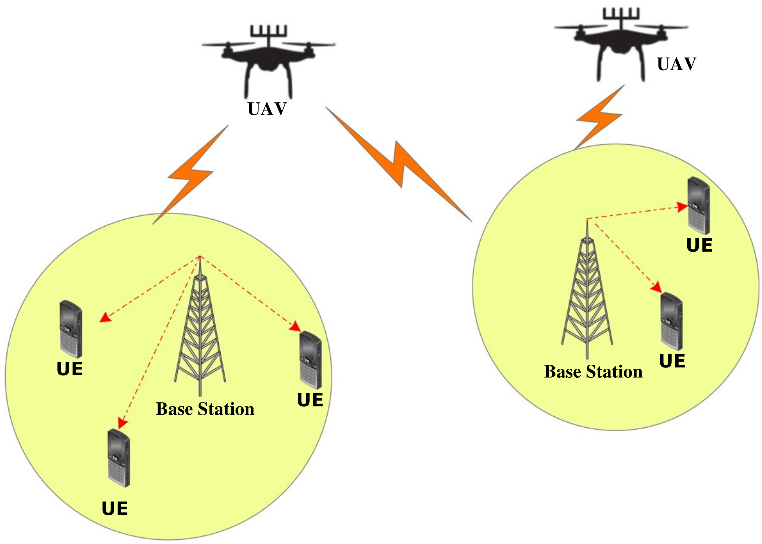


**Fig. 10** NOMA in UAV scenario

by hovering UAV in the NOMA system [36]. A joint user clustering with beamforming strategy is proposed in [36] to minimize the transmission power and meet the quality of service requirement of all the users inside a cell. The user clustering problem is solved using the K-means++ method and optimizing beamforming using the semidefinite relaxation (SDR) method for considering imperfect channel state information. An iterative technique is proposed in [32] to optimize the system's minimal sum rate for a UAV-based NOMA network in a limited time.

The basis for user clustering relies on determining the optimal number of users within a cluster, denoted by K. An iterative algorithm is proposed to optimize user clustering and UAV trajectory simultaneously to maximize the sum rate [32]. The author in [66] suggested a technique for calculating user clustering and channel assignment for a specific UAV position based on the optimum resource allocations. In generic Cooperative and cognitive non-orthogonal multiple access (CCR-NOMA), constructing closed-form optimum power and time allocations for network cluster sizes have been investigated. Based on a linear bottleneck assignment (LBA) algorithm, the suggested clustering uses the best data rates and channel assignment approaches. Figure 10 illustrates the typical UAV scenario.

### 4.5 NOMA-based user clustering in other networks

Clustering device-to-device (D2D) links using the same resource blocks for data transmission and reception is critical; an ideal clustering algorithm is infeasible for a practical system because it necessitates an exhaustive search. In a fog radio access network (F-RAN) design, resource allocation is examined to improve the performance of D2D cooperation [67]. The main goal is to increase the device-clusters' end-to-end sum rate while reducing interference between D2D collaboration and the uplink F-RAN via shared resource blocks. The proposed Rate-splitting for the Multi-hop D2D algorithm performs well and improves the sum rate of the network [67]. In [68], a proposal is made for joint optimization of BS clustering and power regulation in NOMA-enabled CoMP transmission within dense cellular networks to maximize the system sum rate. The NOMA group's interference can propagate to other users in the same BS cluster, reducing transmission rates. To iteratively update the BS clustering, a proposed technique based on a successive convex approximation is used to improve the sum rate. In [68], an iterative algorithm is introduced for BS clustering and power allocation, aiming to fulfil the QoS requirements of the users. In [69], a proposed algorithm for distributed user clustering and resource allocation is utilized to create feasible clusters. The author proposed a distributed technique for $\alpha$-fair resource allocation to enhance the spectral efficiency of the NOMA heterogeneous network.

In [52], the investigation of the resource allocation problem in the uplink NOMA system of D2D networks is proposed. They proposed an iterative algorithm to solve the power allocation problem using Karush–Kuhn–Tucker conditions. Modelling of user clustering based on the hedonic coalition game method is also suggested in [52]. Users analyse their preferences to choose coalitions based on utility and coalition value in a Hedonic coalition game. The coalitions are based on the NOMA principle, which maximizes the benefits.

Ambient backscatter communication assisted with NOMA is a promising technology to address the physical layer authentication problems to prevent users from malicious activities [70]. The integrated satellite-unmanned aerial vehicle-terrestrial networks (IS-UAV-TNs) is one of the emerging technologies based on NOMA to improve spectrum efficiency while reducing transmission delay and improving quality of service [71]. The IS-UAV-TNs assisted with RIS uses a deep reinforcement learning approach to serve multiple vehicles by employing the fundamental principle of NOMA to improve spectrum efficiency and interact with real-time environment [72].

## 5 Future research directions

This survey indicates performance advantages and trade-offs that stimulate future research into the presented NOMA-enabled user clustering schemes and technologies. NOMA will be combined with additional advanced multi-antenna systems operating at the higher end of the mm-wave spectrum and THz frequencies in the future. More novel techniques that utilize these properties of mm-wave channels to benefit NOMA cluster formation, using both machine learning and classical optimization, are being envisioned.

In a RIS-NOMA system, the influence of numerous antennas at the receiver on the NOMA user ordering problem and the cluster formation problem is significant and a possible future research direction. In multicell systems, the cause of inter-cluster interference between NOMA clusters by common passive reflectors presents fascinating design difficulties, a challenge that needs to be addressed.

Examining the sum rate performance of an underwater acoustic NOMA system with the joint optimization of power allocation, resource allocation, and user clustering could be an appealing field for future research in underwater communications systems. Applying machine learning to NOMA-enabled systems has numerous benefits, but it also has its drawbacks. The processing power required to perform some of these ML algorithms is one of the significant challenges with ML algorithms. Another improvement area with machine learning algorithms is the vast amount of necessary data, such as CSI, user locations, and so forth, but solely for immediate scheduling considerations.

Several resource allocation challenges in next-generation wireless communications systems have been studied using DRL algorithms [73]. The DRL can solve specific sub-problems for the overall rate optimization objective, similar to how ML clustering was used to solve the user selection sub-problem. Exploring the application of online machine learning-based user clustering methods to address the rate optimization challenges in NOMA is an essential area for future research, as discussed in this paper.

The use of backscatter communication to optimize conventional cooperative NOMA communication is proposed for the 6G network. A Base Station (BS) concurrently transmits data to two NOMA users. Furthermore, this research considers the scenario where the closer user assists in data relay to a more distant user. Simultaneously, a backscatter tag receives a superimposed signal from the BS and the cooperative user, modulates its information, and then reflects it towards both users. The sum rate is significantly improved by employing backscatter-aided NOMA [74].

Due to the expansion of dense networks, they face significant susceptibility to extensive attacks. Therefore, blockchain technology, typically integrated at the application layer, is recommended as an effective security and privacy solution for future 6G networks [75]. The simultaneously transmitting and reflecting reconfigurable intelligent surface (STAR-RIS) assisted NOMA is a promising technology for extremely low power transmission delivering improved sum rates of the network [76].

Other significant works include relay-based NOMA for enhanced spectral efficiency and reliable communication. In [77], the coordinated direct and relay transmission (CDRT)-based NOMA significantly improves the throughput compared to the other relayed-based NOMA. The incremental relaying network with an energy harvesting-based method is used to harvest energy from the source of radio frequency signals to expand the network coverage [78]. The neural network-based simultaneous wireless information and power transfer (SWIPT) relay scheme proposed in [79] maximizes the throughput by using a dynamic power allocation and user selection.

The joint user clustering and resource allocation in NOMA systems are essential for optimizing network performance, achieving higher spectral efficiency, ensuring user fairness, and accommodating a growing number of users and diverse applications for future networks. Tera-Hertz (THz) communication has earned significant attention due to its potential to meet the ever-growing demand for ultra-high data capacity in future networks. Furthermore, integrating advanced techniques such as MIMO and NOMA with multiple antennas has enhanced the network's ability to accommodate more users simultaneously [35].

Satellite aerial-to-ground communication is one of the future research directions. The author in [80] states that Satellite-Aerial-Ground Integrated Networks (SAGINs) have emerged as a promising infrastructure for next-generation wireless networks. The RIS-assisted UAV using DRL reflects the uplink signals to the ground vehicle transmitter and optimizes the system sum rate.

## 6 Conclusion

This research shows the significance of user clustering techniques in NOMA communication in current and future wireless networks. User clustering is a valuable strategy for improving network throughput, spectral efficiency, and user fairness, especially in dense networks. It helps mitigate channel access problems and is particularly relevant in emerging technologies like the IoT, UAV, and RIS in 5G and beyond communication networks.

This survey paper highlights user clustering techniques, machine and non-machine learning techniques, and their applications in different scenarios. They emphasize that as the number of users in wireless networks grows, user clustering becomes essential for effectively managing network resources. However, finding an optimal user clustering solution becomes challenging with many users, leading researchers to propose low-complexity methods. This survey paper motivates the researcher to get a deep understanding of the solution to the user clustering problem in the NOMA network, emphasizing their role in improving downlink sum rate performance. Moreover, this paper discusses the role of machine learning in addressing user clustering and power allocation challenges in future NOMA-enabled networks, along with presenting a set of potential research directions.

**Abbreviations**

| | |
|---|---|
| NOMA | Non-orthogonal multiple access |
| MISO | Multi-input single output |
| MIMO | Multi-input multi-output |
| UAV | Unmanned aerial vehicles |
| IoT | Internet of things |
| 5G | 5th generation |
| mm-wave | Millimetre wave |
| PD-NOMA | Power domain non-orthogonal multiple access |
| CSI | Channel state information |
| DRL | Deep reinforcement learning |
| RIS | Reconfigurable intelligent surface |
| D2D | Device to device |
| ML | Machine learning |
| BS | Base station |

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**Availability of data and materials**
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**Code availability**
Not applicable.

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

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