IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 23, 2020, accepted September 21, 2020, date of publication September 29, 2020, date of current version October 12, 2020.
Digital Object Identifier 10.1109/ACCESS.2020.3027777

Efficient User Clustering Using a Low-Complexity Artificial Neural Network (ANN) for 5G NOMA Systems

S. PRABHA KUMARESAN[1], CHEE KEONG TAN[2], AND YIN HOE NG[1]
[1]Faculty of Engineering, Multimedia University, Cyberjaya 63100, Malaysia
[2]School of Information Technology, Monash University Malaysia, Subang Jaya 47500, Malaysia
Corresponding author: Chee Keong Tan (tan.cheekeong@monash.edu)

This work was supported by the Multimedia University under Grant MMUI/170084.

ABSTRACT Non-orthogonal multiple access (NOMA) has gained considerable interest from the 3GPP community as a potential radio access strategy for the future fifth-generation (5G) wireless networks. Compared to orthogonal multiple access (OMA), NOMA is more efficient from the perspective of throughput performance making it more favorable for 5G systems. Existing NOMA techniques merely offer a rigid user grouping without exploring channel heterogeneity and diversity to cluster users, resulting in a poor throughput performance. An adaptive user clustering (AUC) approach has been proposed to search through all possible combinations to obtain the best clusters with the highest throughput. This scheme exploits the channel diversity of users to maximize throughput, however, the brute-force search (B-FS) method to find the optimal combinations results in a prohibitive complexity. In this paper, a novel artificial neural network (ANN) approach is proposed for user clustering in the downlink of the 5G NOMA system in order to maximize throughput performance at an acceptable complexity. In the proposed strategy, ANN model is first trained with the historical dataset, which contains the transmitting powers and channel gains of the downlink NOMA users, along with the information of the corresponding clusters which maximize the throughput performance of the system. Next, validation is performed to tune the values of hyper-parameters such as learning rate, length of training data, and epoch learned during training to validate cluster formation and to avoid over-fitting of the model. Finally, the ANN model is tested with the learned parameters and tuned hyper-parameters, to predict the formation of clusters and to evaluate the accuracy of the model. Simulation results demonstrate that the proposed scheme is able to obtain a significant reduction in terms of complexity with a performance of 98% for throughput (near-optimal throughput performance) when compared with the optimal approaches.

INDEX TERMS Artificial neural network, low-complexity, machine learning, non orthogonal multiple access (NOMA), throughput maximization.

I. INTRODUCTION

over the decades, cellular networks have been seeking innovative multiple access standards to provide seamless and ubiquitous connectivity for a broad variety of data-centric and bandwidth-hungry mobile services that vary from the services supported by the earlier generations. The next generation known as the fifth-generation (5G) [1] cellular network is envisioned as the catalyst to open doors for various inventive technologies and services such as augmented reality (AR), Internet of Things (IoT), cloud computing, blockchain-enabled mobile security, and artificial intelligence (AI). These emerging technologies give rise to the scarcity of the radio spectrum which is considered to be the most precious resource in 5G networks.

To fulfill the massive spectral demands caused by an enormous technological paradigm shift from 4G to 5G, multiple access schemes play a pivotal role to ensure all 5G users could be able to simultaneously utilize those advanced technologies and services promised in 5G networks with a satisfactory

The associate editor coordinating the review of this manuscript and approving it for publication was Sunil Karamchandani.

quality of service (QoS) and without any latency. Fundamentally, multiple access is a channel access method that allows more than two mobile users to establish connections to a base station (BS) by sharing the same radio resources, either in the time or frequency domain. The famous multiple access variant known as orthogonal multiple access is the key to 4G success. In OMA-based 4G systems, each mobile user is exclusively allocated with a subset of sub-channels to avoid co-channel and adjacent channel interference as the channel accessibility of users is orthogonal in nature. However, ensuring the orthogonality of resources shared by the users prevent resource sharing, thus OMA-based systems are unable to accommodate an unprecedentedly huge number of users in 5G networks. As a result, a more efficient multiple access scheme is considered during the 5G standardization, leading to the emergence of non-orthogonal multiple access (NOMA) [2] which is endorsed to replace OMA.

In short, NOMA technique is designed to support multiuser transmission by allowing several users to share identical resource block through superposition coding (SC) method at the users' transmitters. The interference is introduced at the receivers when the super-imposed signals are being segregated. Fortunately, the implementation of successive interference cancellation (SIC) technique at the receivers helps the users to recover their own desired signals without any corruption resulted from the interference.

A. PRIOR WORKS

The concept of NOMA has been initially discussed for 5G cellular systems in [3], [4] and its excellent implementation and performance have been first revealed in the same work. NOMA's attractive benefits and features particularly for 5G networks have started to garner attention from many researchers from academia as well as industries [5]–[9]. The NOMA techniques can generally, be categorized into two variants, i.e., 1) power-domain and 2) code-domain. This paper mainly focuses on the power-domain NOMA technique for a downlink 5G network where a distinct power is assigned to each downlink connection from BS to different users. Subsequently, the BS super-imposes the desired signals to multiple users with different power coefficients and transmits the combined signal on the same frequency sub-channels. The power allocation for each downlink connection is determined by their respective channel gains (from the BS to users) where a user with the poorer channel gain is allotted with higher transmission power than the one which has a better channel gain. At the receiver side, the user with the higher power can immediately recover its signal by treating other users' signals as noise without needing SIC. On the other hand, SIC is implemented to assist those users with lower power allocations to retrieve their desired signal by eliminating unwanted signals from the received super-imposed signals.

To effectively employ SIC at the receivers, user clustering is crucial because different ways of grouping the NOMA users with different channel conditions may lead to different power allocation strategy and this eventually affects the overall system throughput and SIC implementation. A two-user NOMA model served by a single carrier and a multi-user NOMA model serving an arbitrary number of users in each subcarrier has been discussed in [10] by providing insight into the recent research work carried out in analyzing the allocation of resources and performance gain in terms of spectral efficiency and outage probability. The implementation of power-domain NOMA has been evaluated in [11] where the user grouping problem in NOMA has been investigated using predefined user clustering and fixed per group power distribution schemes. In [12], the effects of user pairing on the performance of NOMA-based cognitive radio networks with fixed power allocation have been investigated. The performance of NOMA in downlink scenario with random deployment of users was investigated in [13] and it has been shown that NOMA achieves enhanced performance in terms of ergodic sum rate. The resource allocation algorithm for a multi-carrier NOMA systems with a full duplex BS was examined in [14] to maximize the weighted sum throughput of the system using monotonic optimization. As the technique suffers from high computational complexity, a suboptimal algorithm based on successive convex optimization was suggested to strike a balance between system throughput and user fairness. Resource allocation for downlink NOMA systems focusing on user-pairing and power allocation algorithms is presented in [15]. In this work, the capacity gain among the NOMA clusters are controlled using random pairing (RP) and divide and next largest difference based user pairing algorithm (D-NLUPA). The effects of power allocation on the user fairness of downlink NOMA systems were investigated in [16] under the assumption of perfect channel state information (CSI) and average CSI feedback. Besides that, a low-complexity power allocation scheme that yields the optimal solution was also developed to ensure high user fairness.

Dynamic user clustering method together with its associated power allocation scheme has been proposed in [17] to maximize the sum-throughput performance of a NOMA system by solving the formulated mixed-integer non-linear programming problem based on Karush–Kuhn–Tucker (KKT) optimality conditions. In this work, the user clustering has been extended to group a larger number of users but the limitation of this clustering method is that the cluster size is fixed to a certain number which makes the clustering rigid. To address this issue, adaptive user clustering (AUC) based on Brute-force search (B-FS) method has been proposed in [18] to fully explore the channel heterogeneity and diversity to group "effective" users together. The results have demonstrated that the cluster size should not be fixed and it might vary tremendously depending on the users' channel conditions. This work explores all combinations of user grouping to search for the best grouping that yields the maximum total throughput. Nonetheless, B-FS method has incurred a very high computational cost which renders it impractical for real-world implementation. However, the throughput performance achieved by the B-FS method can be treated as the theoretical upper-bound performance for any upcoming AUC schemes. To reduce the complexity due to B-FS, the authors in [19] proposed a particle swarm optimization (PSO)-based AUC which is capable to achieve a near-optimal throughput performance at a lower complexity. But, the limitation of the PSO-based AUC work is that it might occasionally converge too early causing the search space trapped in a local minimum especially when there is a large number of users in the NOMA system.

B. MOTIVATIONS AND CONTRIBUTIONS

Based on the above discussions, a more powerful and adaptive clustering technique that can effectively exploit the channel heterogeneity and diversity is required to group the NOMA users so that the total system throughput can be maximized at an acceptable clustering complexity. Hence, obtaining a globally optimal solution is nontrivial especially in grouping a large number of NOMA users which motivates the application of machine learning (ML) model. Machine learning can be defined as the ability to infer knowledge from user clustering and subsequently to use the knowledge to adapt the behavior of an ML algorithm based on the acquired knowledge. Recent research contributions have shown that the ML provides an effective solution to fast data clustering since various information features of higher dimensionality can be used flexibly [20]. In addition, from a knowledge discovery point of view, it is insightful to design effective algorithms by utilizing the underlying structures of the clustering information. Among the different types of ML algorithms, artificial neural network (ANN) is one of the most powerful ML algorithms that has been used in recent decades in a variety of tasks to model regression analysis and prediction problems due to its imitative nature. The ANN model structures in layers of fashion that can learn and make intelligent decisions on its own. The learning ability and non-linear statistical behavior of ANN display a complex relationship between the inputs and outputs which results in providing responses in the form of predictions. As a result of learning ability, ANN can adapt to the change in itself, and when there is a change in the environment. More precisely, ANN is a complex adaptive system that can change its internal structure based on the information passing through it. Thus adaptive behavior of ANN can be used to provide a solution for enhancing the system performance in grouping a large number of NOMA users by exploiting the learning features in making decisions resulting in acceptable clustering complexity.

However, ANN largely depends on the structure of the data set in the feature space. As a result, it is challenging to apply ANN to learn the user clustering in NOMA systems since the performance directly depends on the properties of selected features. To facilitate the implementation of ANN for user clustering, the features of transmitting power, channel gain, and the information of cluster formation of NOMA users are required to train the model. The data set containing the abovementioned features are obtained by simulation using MATLAB at different random location of NOMA users. The goal of ANN is to learn the clustering information based on the obtained features of the NOMA users and using the learned information to make decisions in predicting the formation of clusters that maximize the throughput performance of the system. The act of making decisions in predicting the cluster formation by the ANN contributes to group the user clusters automatically which results in reducing the clustering complexity as well. Based on the proposed design, our major contributions are summarized as follows:

1) We investigate the optimization problem for the throughput maximization of NOMA systems by designing an efficient user clustering strategy. As this optimization problem suffers from computational complexity, a sub-optimal solution is needed to enable the practical implementation of the proposed technique.
2) We propose a novel ANN-based user clustering framework to implement the NOMA scheme which exploits the transmitting power, channel gain features and user cluster information of the NOMA users. Furthermore, based on learning ability, ANN is used to predict the formation of clusters leads to automatic clustering which can highly reduce the computational complexity and at the same time achieves near-optimal throughput performance.

Simulation results are provided to demonstrate that the proposed ANN-based user clustering framework for NOMA systems outperforms conventional OMA schemes. Moreover, our proposed solution is able to obtain the optimal throughput performance compared to the B-FS method at an acceptable clustering complexity.

C. ORGANIZATION

The remainder of this paper is organized as follows. In Section II, the system model of a downlink NOMA 5G system is introduced. Subsequently, a novel ANN-based user clustering scheme is proposed in Section III. In this section, the working principle of ANN in user clustering is meticulously described and the performance metrics are clearly defined. The performance of the proposed ANN-based user clustering scheme is evaluated in Section IV where the comparison results in terms of throughput analysis, learning rates, epoch, etc. are shown. Based on the observation obtained from the results, conclusion is drawn in Section V.

II. SYSTEM MODEL (NOMA SYSTEM)

Consider a single-cell downlink NOMA system with M number of randomly and uniformly deployed users denoted as $\{U_1, U_2, \ldots.., U_M\}$ communicating with a centralized BS located at the center of the cell. In this context, B is used to denote the overall total bandwidth of this NOMA system and it is partitioned evenly into N number of subcarriers. In this scenario, the BS transmits the multiplexed signal to all the users using the power-domain NOMA technique. The users' distances from the BS are represented accordingly with $\{d_1, d_2, \ldots.., d_M\}$. The channel gain of user m on subcarrier n is denoted by $g_{m,n}$ which is highly dependent on the distance of the user from the BS. In view of this situation, the channel gains of user deteriorate as the distance from the BS to the user increases. In this context, it is assumed that the BS periodically estimates the downlink channel gains on all subcarriers for all users through pilot signals using dedicated and reliable feedback channels from users to the BS without any delay. Besides, the channel variation on each subcarrier is assumed to be relatively slow as compared to the channel estimation rate performed by the BS. With this assumption, the BS can accurately track the CSI for all users on all subcarriers. Similar to the work in [16], we assume that in all cases the perfect CSI is known to the BS.

The BS allocates downlink powers to all users based on their channel gains where the power allocated to the user m on subcarrier n is specified as $p_{m,n}$. Correspondingly, a user m is multiplexed on subcarrier n if and only if $p_{m,n} > 0$. The received signal of user m on subcarrier n can be expressed as,

$$y_{m,n} = \sqrt{p_{m,n}} g_{m,n} x_m + \sum_{l=1, l \neq m}^{M} \sqrt{p_{l,n}} g_{m,n} x_l + \gamma_{m,n} \quad (1)$$

where x_m and x_l are modulated signals and $\gamma_{m,n}$ denotes the additive white Gaussian noise (AWGN) with zero mean and variance of user m on subcarrier n. The term $g_{m,n}$ includes the Rayleigh fading i.e., $g_{m,n} = \frac{h_{m,n}}{\sqrt{1+d_m^{\alpha}}}$, where $h_{m,n}$ denotes the circularly symmetric complex Gaussian distribution within the interval (0, 1), d_m represents the distance between the user m to the BS and α is the the path loss exponent. Let us consider a NOMA system with a remote user U_1 and a neighboring user U_2, where $g_{2,n}$ is higher than $g_{1,n}$. Based on the working principle of NOMA, a user with a better channel condition is always allocated with a lower transmitting power, hence $p_{2,n} < p_{1,n}$.

When more than one users are multiplexed on the same subcarrier the users are sorted in descending order of their channel gain to determine the position of the user m on subcarrier n which can be denoted by $b_n(m)$. In addition, SIC can be employed for the user m having a better channel condition $g_{m,n}$ where the user is capable of decoding its own desired information by first subtracting the signal of user l having weaker channel condition user $g_{l,n}$ which follows the sorted order $b_n(m) < b_n(l)$. In contrast, the weak channel condition user $g_{l,n}$ following the order $b_n(m) > b_n(l)$ considers the signals of the good channel condition $g_{m,n}$ as noise and decodes its own signal directly. The normalized channel gain is represented by $G_{m,n} = \frac{|g_{m,n}|^2}{\sigma_n^2}$ where σ_n^2 denotes the variance of AWGN . Thus, the achievable data rate of user m on subcarrier n can be expressed as:

$$R_{m,n} = Blog_2(1 + \frac{p_{m,n} G_{m,n}}{\sum_{l \in M\{M\}: b_n(l) < b_n(m)} p_{l,m} G_{m,n} + 1}). \quad (2)$$

III. PROPOSED ARTIFICIAL NEURAL NETWORK (ANN) BASED USER CLUSTERING

This section presents the proposed artificial neural network (ANN) based user clustering scheme for the NOMA systems. In our proposed method, the dataset comprises the transmit powers, channel gains, and cluster formation for various deployment scenarios (e.g., different number of users and different user positions), is utilized to train the ANN. More specifically, the training dataset is generated using the optimal B-FS based AUC [18] so that the proposed scheme learns to make the best decision about the optimal formation of user clusters that can maximizes the throughput performance in dynamic scenarios at a resonable computational complexity. Since the training dataset takes into account of the variations of the inputs and outputs of the ANN due to the changes in deployment scenarios, the proposed scheme is only required to be trained once and it will be able to cope with dynamic scenarios without retraining.

As the formation of clusters determines the throughput performance, the numbering of clusters plays a significant role and it should be numbered in a manner that can be easily learned by the network. Therefore, the clusters are numbered based on the smallest value of channel gain that present in each cluster so that it can form a pattern which helps the network to learn about cluster formation. More explicitly, the cluster which contains the user with the smallest channel gain is labeled as one, followed by the cluster containing the user having the second smallest channel gain is considered to be two and so on.

A. STRUCTURE OF THE ANN BASED USER CLUSTERING

Fig.1 depicts the structure of the proposed ANN-based user clustering, which consists of three layers: an input layer, a hidden layer, and an output layer. The input layer is the first layer that receives the data sample s from the entire dataset S where $s \in \{1, 2, \ldots, S\}$ containing transmitting powers $P_{s,m}$ and channel gains $G_{s,m}$ of M users where $m \in \{1, 2, \ldots, M\}$. The bias node of the input layer is indicated by b_1 and therefore the total number of the input layer nodes is $2M + 1$. The second layer is the hidden layer that consists of H nodes with one bias node b_2. The features of clustering information from all the input layer nodes $i \in \{1, 2, \ldots, 2M\}$ are connected to h node present in the hidden layer where $h \in \{1, 2, \ldots, H\}$.

The output layer is the final layer and it has M number of nodes denoted by $x \in \{1, 2, \ldots, M\}$, which provides the estimated cluster formation number for each user. The weights which connect input layer nodes to the hidden layer nodes and the weights which connect the hidden layer nodes to the output layer are denoted as w_{ih} and w_{hx}, respectively. More specifically, the weights help in deciding how much influence the input features will have on the cluster formation. On the other hand, bias value is a constant parameter that helps the model in a way that it can best fit for a given dataset.

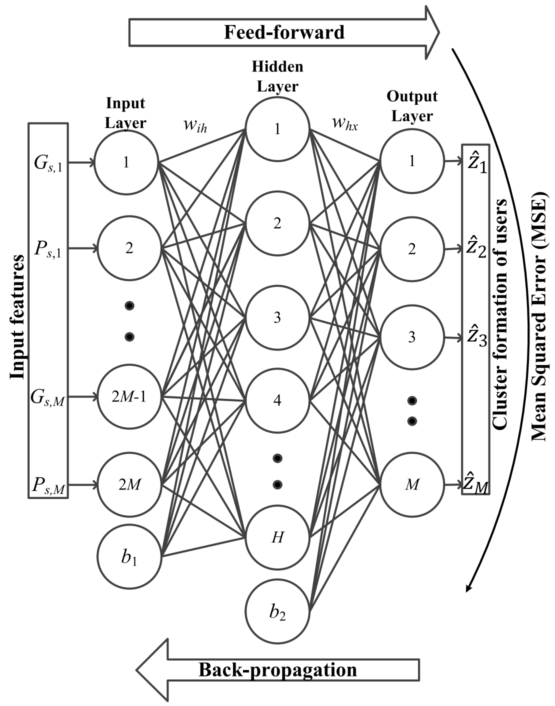

FIGURE 1. The structure of ANN based user clustering scheme for NOMA system.

The input features received by the input nodes are multiplied with the weights of the links, added with the bias value, and passed to an activation function as they move along from the input layer to the hidden layer and from the hidden layer to the output layer. The activation function processed by the hidden layer and output layer are rectified linear unit (ReLu) denoted as φ_h and linear activation function denoted as φ_x, respectively. The ReLu function is linear for values greater than zero. Yet, it is a nonlinear function as negative values are always output as zero. As the function is linear for half of the input domain and nonlinear for the other half it is referred to as a piecewise linear function. Therefore, for positive input values, the function results in output of the input directly which leads to activation of the node. For negative input values, the output is zero that means the nodes are not activated. Thus, the relationship between the input features and the cluster information is preserved using the linear nature of ReLu that makes the model easier to optimize with gradient-based methods. Hence ReLu is computationally efficient and helps the model in generalizing well to achieve better cluster formation for any number of users. The linear activation function is used in the output layer as it allows multiple outputs proportional to the input. Due to its attractive nature of simplicity, it is used in the output layer that helps in obtaining the cluster formation of NOMA users.

Algorithm 1 summarizes the training phase of the proposed ANN-based user clustering scheme. During the training phase feed-forward computation and backward propagation for weight adjustment will be performed. The process of feed-forward computation and backward propagation are detailed in Sections III(B) and III(C), respectively. Once the ANN is trained, testing will be executed as described in Algorithm 2.

Algorithm 1 Training Algorithm for ANN Based User Clustering Scheme

Input: $\{G_{s,1}, G_{s,2}, G_{s,3}, \ldots, G_{s,M}\}$ and $\{P_{s,1}, P_{s,2}, P_{s,3}, \ldots, P_{s,M}\}$ represent the channel gain information and transmitting power of NOMA users respectively.
Output:ANN model

1) Initialize the weights ($w_{((2i-1),h)}$, $w_{(2i,h)}$) and w_{hx}).
2) The input from training data samples is formatted as $\{(G_{s,1}, P_{s,1}, G_{s,2}, P_{s,2}, \ldots G_{s,M}, P_{s,M}), (z_1, z_2, z_3, \ldots, z_M)\}$.
3) Initialize the learning rate α.
4) Feed the *reshape*$(G_{s,1}, P_{s,1}, G_{s,2}, P_{s,2}, \ldots, G_{s,M}, P_{s,M})$ features into the nodes of input layer.
5) **for** $d = 1 : z_M$.
6) Compute v_h and y_h of hidden layer.
7) Compute v_x and $\hat{z}_M$ of output layer.
8) Compute SE of output layer.
9) Compute the derivative error e'_x of output layer.
10) Compute the derivative error e'_h of hidden layer.
11) Adjust the weights for hidden layer and output layer weights using $w_{((2i-1),h)\_A}$, $w_{(2i,h)\_A}$ and w_{hx_A}.
12) **end for**.
13) Repeat steps 4 to 12 for all training data.
14) Compute MSE and repeat steps 4 to 12 until the MSE reaches an acceptable level.
15) Repeat steps 4 to 7 for all validation data.
16) Compute the MSE for validation data samples.

Algorithm 2 Testing Algorithm for ANN Based User Clustering Scheme

Input: $\{G_{s,1}, G_{s,2}, G_{s,3}, \ldots, G_{s,M}\}$ and $\{P_{s,1}, P_{s,2}, P_{s,3}, \ldots, P_{s,M}\}$ represent the channel gains and transmitting powers of NOMA users from testing data samples, respectively.
Output: Cluster formation of users.

1) Feed the reshape testing data samples containing the input features of NOMA users into the ANN model.
2) Process the ANN model by repeating the steps 4 to 7 of Algorithm 1 for all testing data samples.
3) Compute MSE for all the samples based on the cluster formation obtained.
4) Compute the throughput using (2) based on the cluster formation for users obtained.

B. FEED-FORWARD COMPUTATION

This subsection presents the feed-forward computation for ANN based user clustering. The input of the hidden layer node v_h and the output of the hidden layer node y_h can be expressed as

$$v_h = \sum_{i=1}^{M}((G_{s,i} * w_{(2i-1),h}) + (P_{s,i} * w_{2i,h})) + b_1. \quad (3)$$

and

$$y_h = \varphi_h(v_h). \quad (4)$$

respectively. As ReLu is used as the activation function in the hidden layer it deactivates the nodes if the output of the linear transformation is less than zero. Hence, all the nodes are not activated at the same time, and the ouput can be rewritten as,

$$y_h = \max\{0, v_h\}. \quad (5)$$

For the sake of clarity, (5) can be further rewritten as follows:

$$y_h = \begin{cases} 0, & \text{if } v_h \leq 0 \\ v_h, & \text{if } v_h > 0. \end{cases} \quad (6)$$

The input and output of the output layer node are denoted by v_x and z_x, respectively, which can be expressed as

$$v_x = (\sum_{h=1}^{H} y_h w_{hx}) + b_2. \quad (7)$$

$$z_x = \varphi_x(v_x). \quad (8)$$

The predicted cluster formation is then compared with the desired cluster formation to compute the squared error (SE). The SE computed based on the predicted cluster formation $\hat{z}_x$ and the actual cluster formation z_x can be expressed as,

$$SE = \sum_{x=1}^{M}(z_x - \hat{z}_x)^2. \quad (9)$$

The SE can be minimized by back-propagation mechanism, which will be explained in the following subsection.

C. BACK-PROPAGATION AND WEIGHT ADJUSTMENT

The objective of back-propagation mechanism is to minimize the SE. Firstly, generalized delta rule is applied to get the value of updating the weights to be used for the output and hidden layer which are denoted by δ_x and δ_h and can be expressed as,

$$\delta_x = \varphi'_x(v_x)e'_x. \quad (10)$$

$$\delta_h = \varphi'_h(v_h)e'_h. \quad (11)$$

where φ'_x and φ'_h denote the derivative of the linear activation and ReLu function upon v_x and v_h, respectively. On the other hand, e'_x and e'_h represent the derivative of the SE and $\sum_x(\delta_x * w_{hx})$ respectively. Next, δ_x and δ_h are multiplied by the learning rate α to determine how much weight is changed every time and its value ranges between 0 and 1. If the value of α is too high, the output wanders around the expected solution and if the value of α is too low, the output fails to converge to an acceptable solution. Therefore, the value of α should be carefully chosen. The weights updates for the output and hidden layer are expressed as $(\alpha * \delta_x * y_h)$ and $(\alpha * \delta_h * (G_{s,m}))$, $(\alpha * \delta_h * (P_{s,m}))$.

Once the weights updates are calculated, the next task is to adjust the weights in hidden and output layer. The adjustments of weights performed using stochastic gradient descent (SGD) for the hidden layer and output layer are denoted by $w_{((2i-1),h)\_A}$, $w_{(2i,h)\_A}$ and w_{hx_A} and can be expressed as,

$$w_{((2i-1),h)\_A} = w_{((2i-1),h)} + (\alpha * \delta_h * (G_{s,m})). \quad (12)$$

$$w_{(2i,h)\_A} = w_{(2i,h)} + (\alpha * \delta_h * (P_{s,m})). \quad (13)$$

$$w_{hx\_A} = w_{hx} + (\alpha * \delta_x * y_h). \quad (14)$$

As SGD is an iterative mechanism, it adjusts the weight by constantly updating it to minimize the SE calculated for each training data. The number of times that the learning algorithm work through the entire data set is measured by the hyper-parameter of SGD, namely the epoch. The accuracy of the model is assessed after training, by using the validation dataset. The samples of validation data provide an unbiased evaluation of a model that fit on the training data set while tuning model's hyper-parameters. The accuracy of the model is measured using mean square error (MSE), which can be expressed as,

$$MSE = \frac{1}{S}\sum_{x=1}^{S}(z_x - \hat{z}_x)^2. \quad (15)$$

If the MSE is high, then the training data needs to undergo more than one epoch until MSE reaches an acceptable level. After the network completes the training and validation, the model can be tested using testing dataset.

The performance of ANN can be quantified in terms of accuracy as follows:

$$\text{Accuracy} = \frac{\text{Number of correctly predicted samples}}{\text{Total number of samples}}. \quad (16)$$

Since the underlying architecture of the proposed technique is ANN, the computational complexity of the proposed scheme is similar to that of the ANN and it can be expressed as $\mathcal{O}(Klog_2(K))$, where K denotes the total number of nodes present in the network [21]. Unlike the B-FS method [18] which requires prohibitively high complexity to attain optimality, the proposed scheme is a pragmatic user clustering solution for 5G NOMA systems due to its low computational cost.

IV. NUMERICAL RESULTS AND DISCUSSIONS

In this section, we evaluate the throughput performance of the proposed ANN-based user clustering scheme via MATLAB simulation. More specifically, the throughput and the MSE performance of the proposed scheme for different settings of learning rate, lengths of the training samples, and number of epochs are investigated. The throughput performance is utilized to demonstrate the effectiveness of the proposed user clustering scheme as compared to various existing techniques. Besides that, the MSE performance metric is chosen because this metric is a commonly used parameter for ANN model to find the most efficient learning rate and optimal number of epochs at different validation and training errors. We also intend to analyze the performance of the proposed scheme for different network sizes (different number of users) to investigate the scalability of the proposed scheme. The throughput performance of the proposed technique is benchmarked with the conventional OMA scheme, B-FS based clustering [18], RP-NOMA [15] and D-NLUPA-NOMA [15].

The simulation setup for the proposed scheme is presented in Table 1.

TABLE 1. Simulation setting.

Parameter	Value
Number of layers	3
Size of data	12000
Length of training data	6000, 7200, 8400
Length of validation data	1800
Length of testing data	1800
Learning rate	0.1, 0.02, 0.01, 0.002, 0.001
Number of NOMA users	12
Number of input layer nodes	24
Number of hidden layer nodes	24
Number of output layer nodes	12

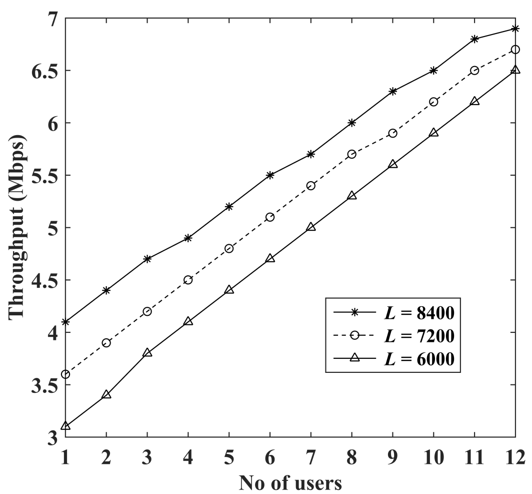

FIGURE 2. Throughput analysis of different length of training samples (L) and different number of users.

Fig. 2 shows the throughput performance of the proposed scheme for different lengths of training samples and different number of users. In general, the throughput performance improves with increasing number of users as the subcarriers are shared among the users present in the same cluster. Besides that, it can be seen that the case for 8400 training data samples attains higher throughput as compared to those of 7200 and 6000 of training data samples. This is due to the fact that the number of training samples less than 8400 is insufficient to train the proposed model. For instance, compared to the case of 12 users with 8000 training samples, the throughput performances of 7200 and 6000 training samples for the same number of users are found to degrade by around 16% and 30%, respectively.

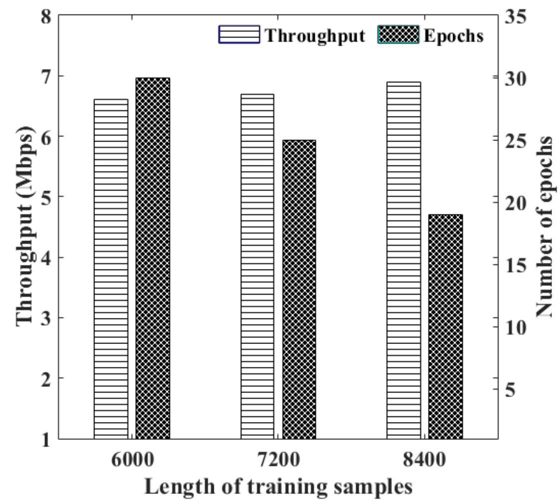

FIGURE 3. Effects of the length of training samples on the throughput performance and the number of epochs required.

In Fig. 3, the effects of the length of training samples on the throughput performance and the number of epochs required are analysed. The number of epochs required for the model to predict the cluster formation decreases with increasing number of training samples. On the contrary, it is observed that throughput performance increases with increasing number of training samples. For example, the model trained with 6000 samples requires more number of epochs, i.e., 30 epochs, to make the error function small which results in predicting the correct formation of user clusters. More number of epochs indicates that the model needs a longer time to learn about the cluster formation of users.

In Fig. 4, the throughput performance is analysed in terms of the number of epochs with respect to different length of training samples. For the case of 6000 training samples, the model needs to undergo 30 epochs to reduce the error between the exact and predicted cluster formation of users so that an acceptable throughput performance could be attained. As a result, the model requires more time to learn about the cluster formation for different number of users. It is also observed that the throughput performance for 6000 training samples with 30 epochs outperforms those of the other setting of epochs considered. This is because increase in the number of epochs reduces the error and this leads to better throughput performance. On the other hand, for the case of 7200 training samples, the best throughput performance is attained by 25 epochs. This is due to the fact that increase in the length of training samples could improve the learning capability of the model which results in error reduction. However, when the number of epochs for 7200 training samples is increased to 30, the throughput performance degrades due to over-fitting of the model. For the same reasons, the model trained with

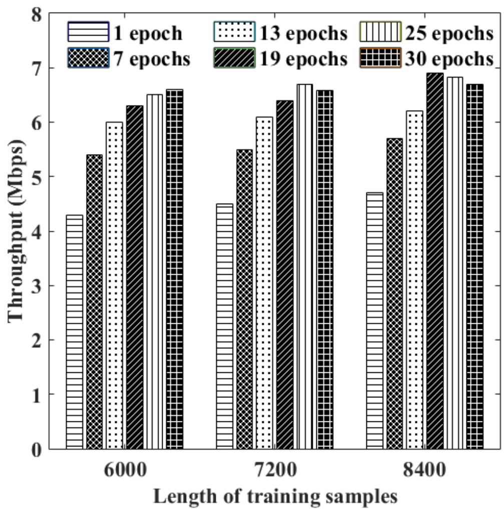

FIGURE 4. Throughput performance at different number of epochs.

8400 samples requires less number of epochs compared to the cases of 6000 and 7200 training samples, i.e., 19 epochs only, to attain the best throughput performance.

Figs. 5 and 6 illustrate the impact of the learning rate and the number of users on the throughput and MSE performance for 1 and 19 epochs, respectively. As expected, the throughput performance for different number of users increases as the learning rate reduces. On the other hand, the MSE reduces with a smaller number of learning rates. At learning rate of 0.1, the model finds it difficult to control the speed of learning which leads to the occurrence of larger error and throughput degradation. On the other hand, at smaller learning rates, the model finds it easier to control the speed of learning and it also improves the prediction of cluster formation which results in better throughput performance.

To enhance the accuracy of the prediction, the model needs to be sufficiently trained so that the error function can be minimized. This can be achieved by increasing the number of epochs to 19 as shown in Fig. 6. From the Fig. 6, it is apparent that the model can attain better MSE and throughput performance at a learning rate of 0.001.

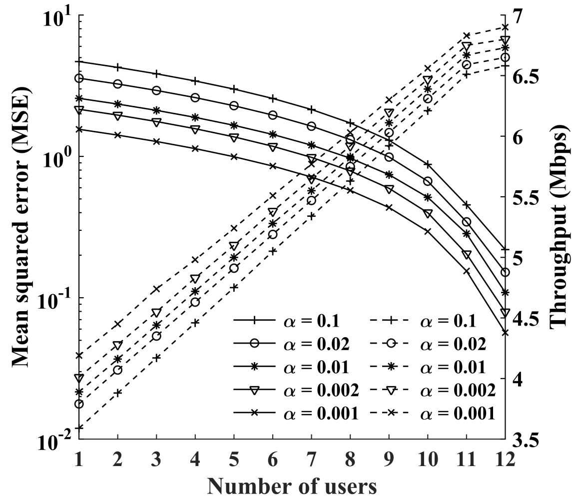

FIGURE 6. MSE and throughput performance of ANN at different learning rate for 19 epochs.

Fig. 7 provides an insight into the effects of the number of epochs on the MSE of training and validation samples at different learning rates. As expected, the MSE for the learning rate of 0.001 is smaller than that of the 0.1. It is noteworthy that the training and validation errors reduce with an increasing number of epochs till 19 epochs. When the number of epochs is further increased beyond 19 epochs, the validation error increases due to over-fitting of the model. Hence,

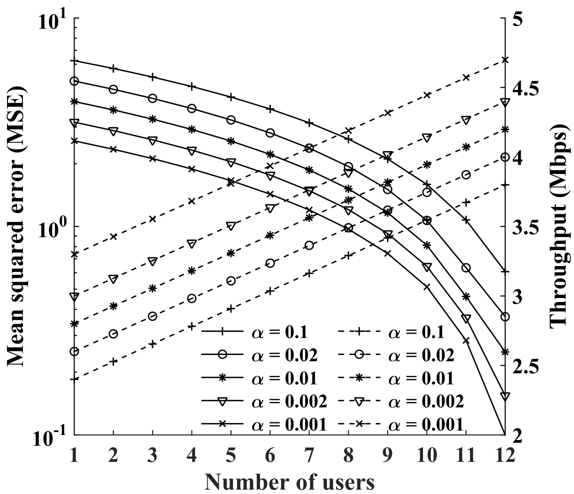

FIGURE 5. MSE and throughput performance of ANN at different learning rate for 1 epoch.

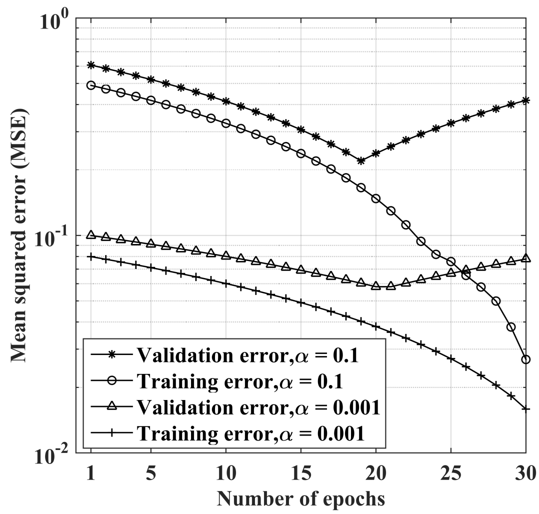

FIGURE 7. Effects of learning rate on the MSE of training and validation samples at different number of epochs.

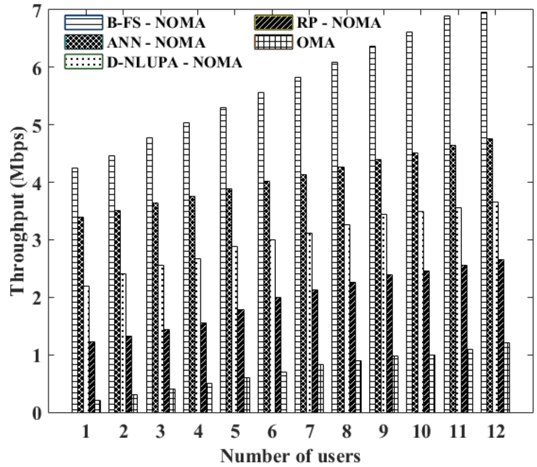

FIGURE 8. Throughput performance of ANN at a learning rate of 0.001 at 1 epoch with respect to the different number of users.

the optimal number of epochs for the case of 8400 training samples with 1800 samples for validation and 1800 samples for testing is found to be 19. It is also observed that at 19 epochs, the training error is close to the validation error thereby this makes the model a good fit for predicting the cluster formation which in turn results in the near-optimal throughput performance.

In Fig. 8, the throughput performance of ANN for different number of users is compared with those of the existing B-FS based clustering, RP, and D-NLUPA in NOMA and OMA systems. The proposed ANN model is trained and validated using 1 epoch with 8400 training samples and 1800 validation samples, respectively. During the testing stage, new data samples for different users are fed into the trained model to predict the cluster formation at the learning rate of 0.001. Based on the cluster formation predicted, the throughput is computed and compared in Fig. 8. From the figure, it is evident that the throughput performance of ANN significantly outperforms the RP, D-NLUPA, and OMA but it is much inferior compared to the B-FS method.

Fig. 9 shows the throughput performance of ANN at 19 epochs. More specifically, the training samples are fed into the model 19 times to reduce the error between the actual and predicted cluster formation. Learning rate of 0.001 is adopted to enable the model to attain the near-optimal throughput performance as compared to B-FS. As shown in the Fig. 9, the proposed ANN-based user clustering scheme is capable to achieve near-optimal throughput performance if the ANN model is well trained.

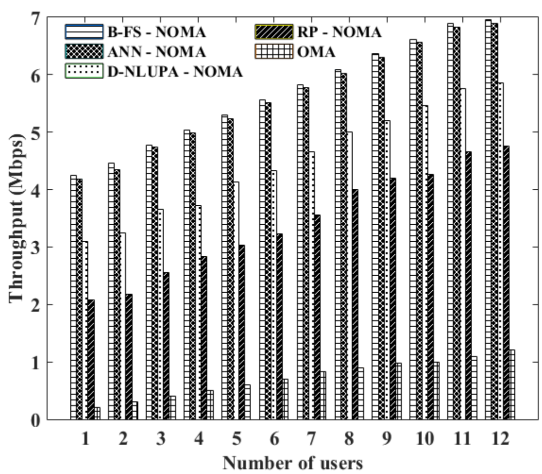

FIGURE 9. Throughput performance of ANN at a learning rate of 0.001 for 19 epochs with respect to the different number of users.

V. CONCLUSION

In this paper, we propose an effective ANN-based user clustering NOMA system for different number of users, which is trained with channel gain and transmitting power of NOMA users to learn about the cluster formation among the users that maximize the throughput performance. Unlike the existing approaches, the proposed scheme automatically groups the users into clusters based on the decision obtained during the training process which results in near-optimal throughput performance. The throughput and MSE performance of the proposed scheme is investigated and the effects of various parameters such as learning rates, number of epochs, and number of users are examined. Numerical results show that the proposed scheme significantly improves the throughput performance of the OMA and it only exhibits slight throughput degradation as compared to the optimal B-FS while attaining a lower computational complexity. This work has demonstrated that the proposed ANN model is a viable technique to tackle the NOMA user clustering problem in 5G networks. For future work, it is worthy to consider the proposed ANN scheme in clustering NOMA users in 5G systems employing a multiple-input-multiple-output (MIMO) antenna as MIMO is one of the key enabling technologies for 5G systems.

REFERENCES

[1] J. Boccuzzi, "Introduction to cellular mobile communications," in *Multiple Access Techniques for 5G Wireless Networks and Beyond*, M. Vaezi, Z. Ding, and H. V. Poor, Eds. Berlin, Germany: Springer, 2019.

[2] W. S. Vicent Wong, R. Schober, D. W. K. Ng, and L.-C. Wang, *Key Technologies for 5G Wireless Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2017.

[3] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for cellular future radio access," in *Proc. IEEE 77th Veh. Technol. Conf. (VTC Spring)*, Jun. 2013, pp. 1–5.

[4] A. Li, Y. Lan, X. Chen, and H. Jiang, "Non orthogonal multiple access (NOMA) for future downlink radio access of 5G," *IEEE China Commun.*, vol. 12, pp. 28–37, Dec. 2015.

[5] S. M. R. Islam, N. Avazov, O. A. Dobre, and K.-S. Kwak, "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 721–742, 2nd Quart., 2017.

[6] Z. Ding, X. Lei, G. K. Karagiannidis, R. Schober, J. Yuan, and V. K. Bhargava, "A survey on non-orthogonal multiple access for 5G networks: Research challenges and future trends," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2181–2195, Oct. 2017.

[7] L. Dai, B. Wang, Y. Yuan, S. Han, I. Chih-lin, and Z. Wang, ''Non-orthogonal multiple access for 5G: Solutions, challenges, opportunities, and future research trends,'' *IEEE Commun. Mag.*, vol. 53, no. 9, pp. 74–81, Sep. 2015.

[8] Y. Liu, Z. Qin, M. Elkashlan, Z. Ding, A. Nallanathan, and L. Hanzo, ''Nonorthogonal multiple access for 5G and beyond,'' *Proc. IEEE*, vol. 105, no. 12, pp. 2347–2381, Dec. 2017.

[9] K. Higuchi and A. Benjebbour, ''Non-orthogonal multiple access (NOMA) with successive interference cancellation,'' *IEICE Trans. Commun.*, vol. E98-B, no. 3, pp. 403–414, Mar. 2015.

[10] Z. Wei, J. Yuan, D. W. K. Ng, M. Elkashlan, and Z. Ding, ''A survey of downlink non-orthogonal multiple access for 5G wireless communication networks,'' *ZTE Commun.*, vol. 14, no. 4, pp. 17–25, Oct. 2016.

[11] A. Benjebbour, A. Li, Y. Saito, Y. Kishiyama, A. Harada, and T. Nakamura, ''System-level performance of downlink NOMA for future LTE enhancements,'' in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2013, pp. 66–70.

[12] M. Al-Imari, P. Xiao, M. A. Imran, and R. Tafazolli, ''Uplink non-orthogonal multiple access for 5G wireless networks,'' in *Proc. 11th Int. Symp. Wireless Commun. Syst. (ISWCS)*, Aug. 2014, pp. 781–785.

[13] Z. Ding, Z. Yang, P. Fan, and H. V. Poor, ''On the performance of non-orthogonal multiple access in 5G systems with randomly deployed users,'' *IEEE Signal Process. Lett.*, vol. 21, no. 12, pp. 1501–1505, Dec. 2014.

[14] Y. Sun, D. W. K. Ng, Z. Ding, and R. Schober, ''Optimal joint power and subcarrier allocation for full-duplex multicarrier non-orthogonal multiple access systems,'' *IEEE Trans. Commun.*, vol. 65, no. 3, pp. 1077–1091, Mar. 2017.

[15] S. M. R. Islam, M. Zeng, O. A. Dobre, and K.-S. Kwak, ''Resource allocation for downlink NOMA systems: Key techniques and open issues,'' *IEEE Wireless Commun.*, vol. 25, no. 2, pp. 40–47, Apr. 2018.

[16] S. Timotheou and I. Krikidis, ''Fairness for non-orthogonal multiple access in 5G systems,'' *IEEE Signal Process. Lett.*, vol. 22, no. 10, pp. 1647–1651, Oct. 2015.

[17] 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*, vol. 4, pp. 6325–6343, 2016.

[18] S. P. Kumaresan, C. K. Tan, C. K. Lee, and Y. H. Ng, ''Adaptive user clustering for downlink nonorthogonal multiple access based 5G systems using Brute-force search,'' *Trans. Emerg. Telecommun. Technol.*, to be published, doi: 10.1002/ett.4098.

[19] S. P. Kumaresan, C. K. Tan, C. K. Lee, and Y. H. Ng, ''Low-complexity particle swarm optimization based adaptive user clustering for downlink non-orthogonal multiple access deployed for 5G systems,'' *World Rev. Sci., Technol. Sustain. Develop.*, vol. 1, no. 1, p. 1, 2020, doi: 10.1504/WRSTSD.2020.10030143.

[20] D. A. Awan, R. L. G. Cavalcante, M. Yukawa, and S. Stanczak, ''Detection for 5G-NOMA: An online adaptive machine learning approach,'' in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2018, pp. 1–6.

[21] P. Orponen, ''Computational complexity of neural networks: A survey,'' *Nordic J. Comput.*, vol. 1, no. 1, pp. 94–110, 1994.

S. PRABHA KUMARESAN received the B.E. degree in electronics and communication engineering from the IFET College of Engineering, India, in 2004, and the M.Tech. degree in advanced communication systems from SASTRA University, India, in 2013. She is currently pursuing the Ph.D. degree with the Faculty of Engineering, Multimedia University, Malaysia, under the supervision of Dr. T. C. Keong and Dr. N. Y. Hoe. She was a Lecturer with the Engineering College from 2004 to 2009 and from 2014 to 2015. Her research interests include NOMA, 5G, and optimization techniques.

CHEE KEONG TAN received the B.Eng. degree in electronics (telecommunication), the M.Eng.Sc. degree in wireless communications, and the Ph.D. degree in wireless communications from Multimedia University, Malaysia. He is currently a Senior Lecturer in wireless system design with the School of Information Technology, Monash University, Malaysia. He has carried out projects for telecommunication companies and cellular service providers, which led to the development of two patents on wireless algorithm and protocol design. He is the main contributing authors to more than ten international journal articles. His current research interests include radio resource management, 5G networks, indoor positioning scheme, machine learning, and artificial intelligence.

YIN HOE NG received the B.Eng. degree (Hons.) in electronics engineering and the Master of Engineering Science and Ph.D. degrees from Multimedia University, Malaysia, in 2004, 2008, and 2013, respectively. He is currently a Lecturer with the Faculty of Engineering, Multimedia University. His current research interests include advanced signal processing techniques for digital communication systems, machine learning, and indoor positioning.