Received: 23 June 2022 | Revised: 20 October 2022 | Accepted: 28 November 2022
DOI: 10.4218/etrij.2022-0251

ORIGINAL ARTICLE

ETRI Journal WILEY

Energy-efficient semi-supervised learning framework for subchannel allocation in non-orthogonal multiple access systems

S. Devipriya | J. Martin Leo Manickam | B. Victoria Jancee

Department of Electronics and Communication Engineering, St. Joseph's College of Engineering, Chennai, India

Correspondence
S. Devipriya, Department of Electronics and Communication Engineering, St. Joseph's College of Engineering, Chennai, India.
Email: devipriyasundar91@gmail.com

Funding information
No funds received.

Abstract

Non-orthogonal multiple access (NOMA) is considered a key candidate technology for next-generation wireless communication systems due to its high spectral efficiency and massive connectivity. Incorporating the concepts of multiple-input-multiple-output (MIMO) into NOMA can further improve the system efficiency, but the hardware complexity increases. This study develops an energy-efficient (EE) subchannel assignment framework for MIMO-NOMA systems under the quality-of-service and interference constraints. This framework handles an energy-efficient co-training-based semi-supervised learning (EE-CSL) algorithm, which utilizes a small portion of existing labeled data generated by numerical iterative algorithms for training. To improve the learning performance of the proposed EE-CSL, initial assignment is performed by a many-to-one matching (MOM) algorithm. The MOM algorithm helps achieve a low complex solution. Simulation results illustrate that a lower computational complexity of the EE-CSL algorithm helps significantly minimize the energy consumption in a network. Furthermore, the sum rate of NOMA outperforms conventional orthogonal multiple access.

KEYWORDS
energy efficiency (EE), multiple-input-multiple-output (MIMO), non-orthogonal multiple access (NOMA), resource allocation (RA), semi-supervised learning, subchannel allocation

1 | INTRODUCTION

Most past research efforts have been directed toward developing new standards in fifth-generation (5G) communication systems to accommodate the rapid growth of traffic data volume. Massive multiple-input-multiple-output (MIMO) and non-orthogonal multiple access (NOMA) systems are two potential candidate technologies for the success of 5G and beyond 5G networks [1–4]. Hence, they have been recently researched by the industry and academia. These two techniques interoperate to meet the future demands of Internet of Things (IoT) devices. NOMA has been considered a key candidate technology that supports the transmission of multiple users simultaneously over same spectral resources. It also allows multiple users to be multiplexed on a common channel using superposition coding and successive interference cancelation techniques at a transmitter and a receiver, respectively. In NOMA, multiple user's information is superimposed in a power domain using their corresponding channel gain differences. At the receiver, a self-interference cancelation (SIC) method of detection is implemented for inter-user interference cancelation. NOMA achieves high spectral efficiency, but the receiver complexity increases. Meanwhile, MIMO has been considered a pragmatic scheme to transmit high-speed data streams using a large-scale antenna array. It also helps achieve significant improvement in throughput without any increase in resources (e.g., power and spectrum). Incorporating the concepts of NOMA into MIMO will further improve the sum rate performance of the system. Resource allocation (RA), which represents the main theme of this study, plays a pivotal role in attaining the benefits offered both by MIMO and NOMA.

1.1 | Related works and motivations

1.1.1 | Studies on conventional NOMA

Different key candidate NOMA schemes have been comprehensively investigated in the literature. Moraqa and others [5] demonstrated the impact of power domain NOMA on different enabling communication technologies. They also addressed the maximum achievable rates using optimization techniques. Several smart techniques have been presented to improve the energy efficiency (EE) and end-to-end delays in both uplink and downlink NOMA [6]. A novel low complexity decoding structure, wherein an arbitrary number of users served in a spectrum, was proposed for NOMA [7]. Wan and others [8] introduced a unique NOMA scheme wherein an entire band is divided into different sub-bands. To improve the fair user rate, information symbols that correspond to a fair user rate are transmitted based on a repetition-based scheme in all sub-bands. A cooperative relay-based NOMA system was presented in Wan and others [9], and its outage performance and ergodic sum were analyzed for both decode-and-forward and amplify-and-forward relaying protocols.

1.1.2 | Studies on MIMO-NOMA

An efficient 3D (i.e., time, frequency, and power) RA scheme was proposed for MIMO-NOMA systems [10]. This scheme aims to realize an alternative for NOMA-based relaying protocols. However, an EE maximization problem was formulated, along with a user admission policy [11] for multi-user MIMO-NOMA systems. A multi-dimensional RA problem was formulated to maximize the sum effective capacity of all users in a MIMO-NOMA cluster [12]. Further, an energy-efficient power optimization problem was formulated as a fractional programming problem for a millimeter-wave MIMO-NOMA system and was solved using sequential convex approximations [13].

1.1.3 | Studies on conventional approaches of RA

A joint subchannel and power allocation problem was formulated for a downlink NOMA system, and a suboptimal solution was proposed by utilizing various techniques (e.g., dual-decomposition techniques [14], introducing slack variables [15], geometric programming [16], simulated annealing algorithm, and a sequence convex approximation programming method [17]). A dynamic resource optimization scheme was designed based on minimum transmit power and maximum EE [18, 19]. A heuristic RA was proposed for hybrid NOMA in Shi and others [20]. Subchannel allocation based on matching theory was provided in Zhao and others. [21] for D2D communications.

However, these methods are iterative and hence are convoluted in obtaining a suboptimal solution. Thus, these conventional methods of RA are inefficient for future wireless communication systems. These methods also depend on expert knowledge in modeling such dynamic systems. Thus, the fundamental attribute of a future wireless system is its ability to learn a new model.

1.1.4 | Studies on deep learning-based RA

Motivated by these considerations, new theories, which can improve the performance of RA systems, should be considered. Recently, machine learning (ML) has been proved to be an efficient method in solving complex mathematical problems. To meet the requirements of future wireless systems, the most important task is to enable ML techniques to make intelligent decisions. Deep learning (DL), a branch of ML, learns features from a set of large volumes of labeled training data. In a previous literature [22–26], a deep neural network (DNN) was designed to solve an RA problem. However, these existing studies did not consider the effect of high power consumption on EE. Moreover, the performance of this learning depends on the number of labeled samples, and training a new model is extremely expensive due to the complexity of training data models in a DNN.

Deep reinforcement learning [27, 28], a subset of ML, utilizes the concepts of DL to make decisions from unstructured data. Although it requires less amount of labeled samples, the size of the state space has a major impact on the performance of this algorithm. Most of the existing RA literature is mainly focused on exhaustive search (ES) methods and a DNN model. Nevertheless, a large volume of labeled training datasets should be obtained for a complex space.

1.2 | Contributions

Motivated by futuristic DL technologies, we attempt to fill the gap in the existing literature. In this study, we attempt to reduce the computation time and improve the learning performance by using a finite amount of labeled training samples.

To the best of our knowledge, no studies have explored a subchannel allocation problem for MIMO-NOMA systems using a DL model. The following is the summary of the innovative aspects of this study:

- We propose a multi-dimensional subchannel allocation framework that maximizes the EE for downlink MIMO-NOMA systems.
- To address this optimization problem, we develop an energy-efficient DL framework under the premise of addressing the quality-of-service (QoS) and interference limitations.
- To improve the learning performance of a DL framework, we introduce a semi-supervised learning algorithm, called EE-CSL, that focuses on the problem of lacking labeled data. A co-training-based method of learning is considered for the subchannel allocation.
- To maximize the total sum rate of the system, we formulate a matching algorithm for the initial assignment of subchannel allocation in a semi-supervised learning model. We also attempt to explore the ability of this matching algorithm in improving the overall system performance.
- We demonstrate that the proposed EE-CSL algorithm can achieve better EE performance. We also provide a performance comparison of the proposed framework with several other different schemes. Some useful insights on the significance of the matching algorithm for the proposed subchannel allocation framework are also provided.

The remainder of the paper is organized as follows. System model and mathematical problem formulation are presented in Section 2. Section 3 provides the subchannel allocation framework and solution approach that uses a co-training-based learning scheme. Extensive simulation results are demonstrated in Section 4, and finally Section 5 concludes the paper.

2 | SYSTEM MODEL

Consider a typical downlink MIMO-NOMA-based heterogeneous IoT network wherein a base station (BS) is equipped with N transmit antennas (Figure 1). BS transmits data to multiple receivers, each equipped with N_r receive antennas that receive the desired signal using a successive interference cancelation (SIC) algorithm. To avoid complex beamforming issues, the number of receive antennas should be greater than the number of transmitter antennas ($N_r \geq N$).

Assume that U users are randomly distributed around the BS and they are grouped into N clusters based on a user pairing (UP) strategy. The set of clusters is denoted by $\{1, 2, ..., N\}$. L users exist in a cluster, and NOMA is applied among the users in a cluster. That is, all L users in a cluster utilize the same spectral resources. The users are clustered based on the strength of the channel gains. User sets with higher and poor channel gains are called strong and weak user sets, respectively. Channel gains are sorted in descending order, and users are partitioned into weak and strong users set such that an equal number of users fall in each set. The red line in Figure 1 indicates the boundary between strong and weak user sets. UP is performed based on the binary dislocation principle [29]; that is, the first user in a strong user set is paired with the $(U/2+1)$th user in a weak user set, and the second user in a strong user set with the $(U/2+2)$th user in a weak set until no user is left out. Consider that the total bandwidth of the system be B_T and k be the number of subchannels. It is assumed that a subchannel is occupied by L (maximum of 3) users simultaneously through SIC

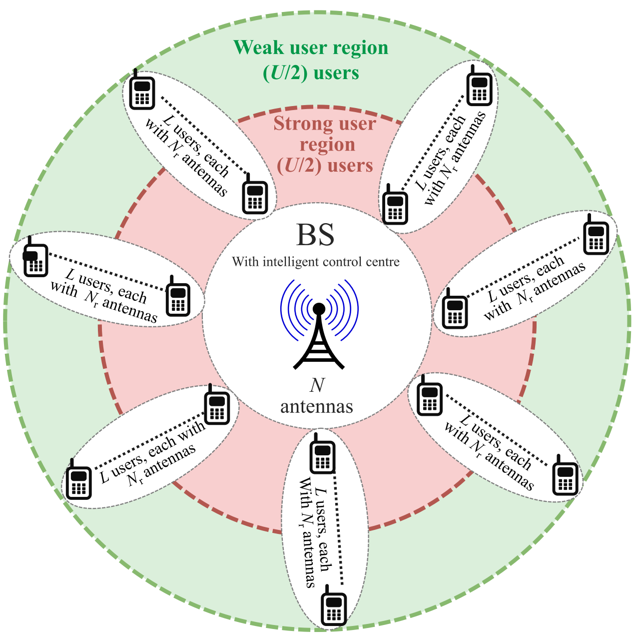

FIGURE 1 System model.

to reduce the interference among users. The bandwidth of a subchannel $b_{n,l}^{k}$represents the subchannel allocation strategy between the lth user in a cluster N and subchannel k. A learning algorithm is implemented at the BS, which decides the subchannel allocation policy of users.

2.1 | System description

Let $P_{N\times N}$ be the precoding matrix used by the BS, which superimposes the intended signals of all L users at the same resource block. This superimposed signal is given as follows:

$$x=PM, \tag{1}$$

where M is the message vector, which can be expressed as follows:

$$M=\begin{bmatrix}\sqrt{p_t\alpha_{1,1}}m_{1,1}+\sqrt{p_t\alpha_{1,1}}m_{1,1}+\dots+\sqrt{p_t\alpha_{1,L}}m_{1,L}\\ \vdots \\ \sqrt{p_t\alpha_{N,1}}m_{N,1}+\sqrt{p_t\alpha_{N,2}}m_{N,2}+\dots+\sqrt{p_t\alpha_{N,L}}m_{N,L}\end{bmatrix}=\begin{bmatrix}M_1\\ \vdots \\ M_N\end{bmatrix},$$

where p_t represents the total transmit power allocated for each cluster and $\alpha_{n,l}$is the power allocation coefficient for user (n,l). Hence, the following power Constraint is satisfied:

$$\sum\nolimits_{l=1}^{L}\alpha_{n,l}\leq 1,\quad \forall n\in N. \tag{2}$$

2.2 | SINR analysis and channel model

Let $H_{n,l}$ be the channel matrix of the lth user in the nth cluster, and it follows Rayleigh fading distribution. The received signal at the lth user in the nth cluster can be given as

$$y_{n,l}^{k}=b_{n,l}^{k}d_{n,l}\left[H_{n,l}^{k}x+n_{n,l}\right], \tag{3}$$

$$\Gamma_{n,l}=\frac{\left|(d_{n,l}H_{n,l})P_n\right|^2\alpha_{n,l}p_t}{b_{n,l}^{k}\left|(d_{n,l}H_{n,l})P_n\right|^2\sum_{j=1}^{L-1}\alpha_{n,j}p_t+\sum_{i=1,i\neq n}^{N}b_{i,l}^{k}\left|(d_{i,l}H_{i,l})P_i\right|^2\alpha_{i,l}p_t+\left|d_{n,l}\sigma_n\right|^2}. \tag{9}$$

where $d_{n,l}$ represents the detection vector of the received signal, $b_{n,l}^{k}$ is the channel assignment index, and $n_{n,l}$ indicates a circularly symmetric complex Gaussian noise vector with variance σ^2. The above equation can be rewritten as follows:

$$\begin{aligned}y_{n,l}^{k}&=b_{n,l}^{k}d_{n,l}H_{n,l}P_nM_n+d_{n,l}H_{n,l}\sum\nolimits_{i=1,i\neq n}^{N}b_{i,l}^{k}P_iM_i+d_{n,l}n_{n,l}\\&=b_{n,l}^{k}d_{n,l}H_{n,l}P_n\sqrt{\alpha_{n,l}p_t}m_{n,l}+b_{n,l}^{k}d_{n,l}H_{n,l}P_n\sum\nolimits_{j=1,j\neq l}^{L}M_{n,j}\\&\quad+d_{n,l}H_{n,l}\sum\nolimits_{i=1,i\neq n}^{N}b_{i,l}^{k}P_iM_i+d_{n,l}n_{n,l}\end{aligned} \tag{4}$$

where P_n is the precoding matrix of the nth cluster. Strong users can be decoded perfectly by the SIC algorithm, and the intra-cluster interference can be suppressed effectively from a weak user's channel gains. By considering the lth user component of a cluster and the rest of the user's component separately, (4) can be written as follows:

$$\begin{aligned}y_{n,l}^{k}&=b_{n,l}^{k}d_{n,l}H_{n,l}P_n\sqrt{\alpha_{n,l}p_t}m_{n,l}+b_{n,l}^{k}d_{n,l}H_{n,l}P_n\sum\nolimits_{j=1}^{L-1}\sqrt{\alpha_{n,j}p_t}m_{n,j}\\&\quad+d_{n,l}H_{n,l}\sum\nolimits_{i=1,i\neq n}^{N}b_{i,l}^{k}P_i\sqrt{\alpha_{i,l}p_t}m_{i,l}+d_{n,l}n_{n,l}.\end{aligned} \tag{5}$$

The signal-to-interference-plus-noise ratio (SINR) $\Gamma_{n,l}$ of the lth user in the nth cluster is defined in (9).

Therefore, the achievable data rate of the lth user in the nth cluster is expressed as

$$R_{n,l}^{k}=\log_2\left[1+\Gamma_{n,l}\right]. \tag{6}$$

We define the achievable sum rate of the system as

$$R_{\text{sum}}=\sum\nolimits_{k=1}^{K}\sum\nolimits_{n=1}^{N}\sum\nolimits_{l=1}^{L}R_{n,l}^{k}. \tag{7}$$

The capacity of the lth user on subchannel k is given as

$$C_{n,l}^{k}=B_{\mathrm{T}}\log_2\left[1+\Gamma_{n,l}\right]\ \forall n\in N, \tag{8}$$

where B_{T} is the total system bandwidth.

2.3 | Problem formulation

The total EE of the system is formulated as

$$E_n = \frac{R_{\text{sum}}}{P_t + P_c}, \tag{10}$$

where P_t is the total transmit power and P_c represents the power consumption by the circuit components, such as mixers, analog to digital converters, and filters. To achieve the maximum EE for a MIMO-NOMA system, this subchannel allocation problem is formulated as follows:

$$\max E_n(t), \tag{11}$$

$$\text{s.t. } C1: \sum_{l=1}^{L} b_{n,l}^{k} \le L \quad \forall k \in K, n \in N$$
$$C2: b_{n,l}^{k} \in \{0,1\} \quad \forall k \in K, l \in L, n \in N$$
$$C3: \sum_{n=1}^{N} \sum_{l=1}^{L} b_{n,l}^{k} = 1 \forall k \in K$$
$$C4: \sum_{n=1}^{N} \sum_{k=1}^{K} b_{n,l}^{k} C_{n,l}^{k} \ge R_{\min} \quad \forall l \in L.$$

Constraint ($C1$) guarantees that the maximum number of users allocated for a subchannel is L, Constraint ($C2$) is the binary subchannel assignment factor, Constraint ($C3$) specifies that at most one subchannel can be assigned for a cluster, and Constraint ($C4$) imposes a minimum data rate requirement on each user in a cluster.

3 | SUBCHANNEL ALLOCATION FRAMEWORK

In this section, we solve the aforementioned optimization problem using a novel co-training-based semi-supervised learning algorithm, called EE-CSL. This problem is a non-convex optimization problem, and its complexity increases with an increase in the number of MIMO-NOMA clusters. A semi-supervised method of learning is utilized here for subchannel assignment, along with co-training [30], which uses two independent classifiers. The initial assignment of the subchannel is generated by the Many-to-one matching (MOM) algorithm, which is provided in the following subsection.

3.1 | MOM algorithm for subchannel allocation

This subsection discusses the MOM algorithm [31] wherein subchannel allocation is considered based on the utility factor. This MOM algorithm is depicted in Figure 2. MIMO-NOMA clusters and subchannels are considered two sets of players. They interact with each other such that their respective utility is maximized. To increase the total sum rate, the dynamic matching between the MIMO-NOMA clusters and subchannels is formulated using the MOM algorithm, and it is addressed using the proposed algorithm. In the MOM algorithm, MOM function Ω is formed such that $|\Omega(k)| \le L, \forall k \epsilon K$, where L is the maximum number of users accommodated in a cluster without interference and $\Omega(k) = \emptyset$ if the subchannel k is not matched to any cluster. To improve the performance of MIMO-NOMA-based heterogeneous IoT networks, the preference lists of user-subchannel groups are formed based on achievable data rate. The set of preference lists of MIMO clusters and subchannels is listed in Table/Figure X.

$$PL = \{P(n_1), P(n_2), \ldots, P(n_N), P(k_1), P(k_2), \ldots, P(k_K)\}. \tag{12}$$

The preference lists of players are created in a decreasing order of their utility on a particular subchannel k. The utility function of a MIMO-NOMA cluster on subchannel k is defined as its achievable data rate when it occupies subchannel k, which is given as

$$\boldsymbol{U}_{n,l}(k) = \sum_{l=1}^{L} \log_2[1 + \Gamma_{n,l}]. \tag{13}$$

As observed from this equation, the utility factor depends on its matched subchannel and the set of MIMO-NOMA clusters that are matched to the same subchannel. As this algorithm provides more preference for larger data rates, the semi-supervised learning method is initialized with an energy-efficient subchannel assignment. This MOM algorithm is depicted in the following figure (Figure 2), and the steps are summarized in Algorithm 1.

Algorithm 1: MOM algorithm for subchannel initialization

Initialize subchannel allocation strategy S
Initialize set $Z(k)$ as users allocated to subchannel k and $\overline{Z}$ as users of unassigned channels
while $\overline{Z} = \emptyset$ do
  for $n = 1{:}N$ do
    if $b_{n,l}^{k} = 1$ **then**
      Select subchannel k^* with best channel conditions
    end if
    if $Z(k^*) \ne L$ **then**
      Let $S_{n,l}^{k^*}$=1; update $Z(k^*)$ and $\overline{Z}$
    end if
    if $z(k^*) = L$ **then**
      Calculate the utility factor of all L users in a cluster who occupy a particular subchannel k^*
    end if
  end for
  Compare the utility function of all clusters, and form a preference list in a descending order of utility function
  Form matching function Ω from the set of k subchannels into the set of all clusters
  Select the cluster that maximizes EE of the kth subchannel and update $Z(k^*)$ and $\overline{Z}$
end while

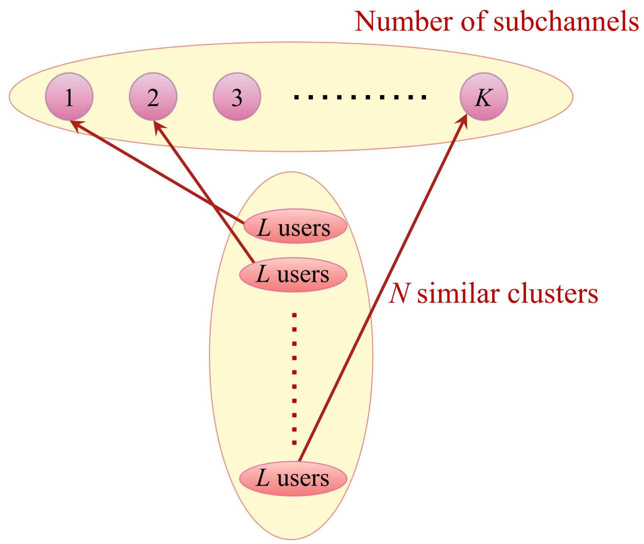

FIGURE 2 Subchannel allocation.

Lemma. *MOM algorithm-based subchannel assignment improves the EE of MIMO-NOMA systems.*

Proof. Let the subchannel assignment for the nth cluster without considering the utility factor (random allocation) be k^*. Specifically, the utility function of the nth cluster in the k^* subchannel is ■

$$\boldsymbol{U}_{n,l}(\Omega^*,k^*) = \sum\nolimits_{l=1}^{L} \log_2\left[1+\Gamma_{n,l}(k^*)\right]. \tag{14}$$

To create a preference list for subchannel allocation, the maximum value of the utility function is considered. After finding a perfect match for the nth cluster in the k^* subchannel,

$$\boldsymbol{U}_{n,l}(\Omega,k^*) = \sum\nolimits_{l=1}^{L} \log_2\left[1+\Gamma_{n,l}(k^*)\right]. \tag{15}$$

As observed from the MOM algorithm,

$$\boldsymbol{U}_{n,l}(\Omega^*,k^*) < \boldsymbol{U}_{n,l}(\Omega,k^*). \tag{16}$$

As the achievable sum rate is increased after finding a better match using the MOM algorithm, EE is also improved.

This MOM algorithm generates a set of labeled datasets $\{\text{label}\} = \{(H_1,S_1),(H_2,S_2),\ldots,(H_{|L|},S_{|L|})\}$. Users that are not assigned with subchannels are called $\{\text{unlabel}\}$ dataset $= \left\{H'_1,H'_2,\ldots,H'_{|U|}\right\}$. Here, H_i represents the channel gain of the ith group, which contains all $h^k_{n,l}$ generated by the ith initialization, and L and U are the number of data samples present in the *label* and unlabel datasets. The concept is to develop a learner $X_s: H \to S$ that can predict the accurate label for an unlabeled input. This learning algorithm is detailed in the subsequent subsection.

3.2 | Co-training-based learning scheme for subchannel assignment

This subsection discusses the subchannel allocation scheme using EE-CSL. This proposed DL scheme is a novel co-training-based semi-supervised learning regression algorithm. This method can have a great practical value if only a small portion of labeled data that are generated by numerical iterative algorithms exists. In this method, only a small portion of existing labeled data is utilized to label the rest of the unlabeled data. This method helps address the problem of the weak generalization ability of the supervised learning method.

To address the subchannel allocation problem, the optimization problem defined in (12) is converted into a loss function in the DL model. The loss function is given as

$$\begin{gathered}\min_{\widehat{S}} \left\|\widehat{S} - \arg\max_s E_n\right\|^2 \\ \text{s.t.} C1 - C4,\end{gathered} \tag{17}$$

where $\widehat{S}$ is the predicted subchannel assignment strategy. A co-training-based learning method is preferred when the labeled data are limited. In this method, two classifiers are trained based on two independent views of data. Then, the labeled data with the most confident predictions of each classifier are selected based on some criteria. Once labeling is completed, the model is updated such that the newly labeled data of one classifier are placed into another classifier's labeled dataset. An important aspect of co-training lies in electing the most confident samples. The most consistent labeled sample in the training data must be the most confident sample. The rule for predicting the most confident sample is defined as follows:

$$\begin{aligned}&\frac{1}{|\text{label}|}\sum\nolimits_{x_i \in \text{label}^s}(S_i - X(G_i))^2 \\ &-\frac{1}{|\text{label}|}\sum\nolimits_{x_i \in \text{label}^s}(S_i - X'(G_i))^2,\end{aligned} \tag{18}$$

where X and X' represent the learning and retrained models, respectively. A retrained model is trained by using the labeled dataset generated from model X. It is included in ideas of Zhou's research [32] that considered initial neural network models should have comparatively large differences. These model differences are evaluated using different neural network parameters and different hidden layers. Hence, two different views exist, and each sample can be accurately classified from each view alone. The proposed co-training-based semi-supervised DL algorithm for subchannel allocation is outlined in Algorithm 2.

Algorithm 2: Co-training-based semi-supervised learning scheme for subchannel assignment

Input: Labeled and unlabeled datasets of subchannel allocation $\{label\}$ & $\{unlabel\}$, number of iterations I_{max}, and number of neurons in hidden layer n_1, n_2

Output: Trained learners with labeled datasets

$$\boldsymbol{X_H^s} = \frac{\mathbf{1}}{\mathbf{2}}\left[\boldsymbol{X_1^s(H)} + \boldsymbol{X_2^s(H)}\right]$$

Training neural networks $\boldsymbol{X_1, X_2}$:
(1) Obtain a set of labeled training samples from the output of algorithm 1.
(2) Develop a neural network framework for two different models X_1, X_2 based on the parameters defined in Table 1.
(3) Initialize the learning and loss rates. Weight updation is initialized using Xavier's method.
(4) Train the developed network X_1, X_2 separately to approximate problem (11)
(5) Update weight w and the output of each layer.
(6) Obtain the output $label$ and $unlabel$ datasets.
Co-training:
Randomly select a subset $\text{unlabel}'$ of size s from the unlabeled dataset unlabel.
repeat
for $j = 1$ and 2 do
for each $h_u \in \text{unlabel}'$ do

$$\hat{S}_u \leftarrow X_j^s(H_u)$$

Train network models $X_j^{s'}$ using datasets $\text{label}_j^s \cup \{(H_u, \hat{S}_u)\}$

$$\delta_{H_u}^s = \sum_{H_i \in \text{label}_j^s} \left[S_i - X_j^s(H_i)\right]^2 - \left[S_i - X_j^{s'}(H_i)\right]^2$$

end for
if there exists $\delta_{H_u}^s > 0$, **then**

$$\hat{H}_j^s = \arg\max_{H_u \in \text{unlabel}'_s} \delta_{H_u}^s$$
$$\hat{S}_j = X_j^s(\hat{H}_j^s)$$
$$\omega_k = \{(\hat{H}_j^s, \hat{S}_j)\}$$
$$\text{unlabel}' = \text{unlabel}' - \omega_k$$

else

$$\omega_k = \emptyset$$

end if
end for

$$\text{label}_1^s \leftarrow \text{label}_1^s \cup \omega_2, \text{label}_2^s \leftarrow \text{label}_2^s \cup \omega_1$$

if one of label_1^s and label_2^s changes, **then**
Update neural network models X_1^s and X_2^s
Fill up $unlabel'$ to set s by randomly picking
end if
Until converges or reaches the maximum number of iterations $I_{\max}$

3.3 | Complexity analysis

This subsection discusses the asymptotic time complexity of the proposed EE-CSL algorithm, which is based on co-training-based semi-supervised learning algorithm. The time complexity of a neural network can be represented by floating-point operations (FLOPs). The time complexity of the proposed EE-CSL algorithm is computed as follows:

In general, the number of FLOPs for each layer of a neural network depends on the dimension of the input and output. The number of FLOPs for each layer of the neural network is expressed as follows:

$$\text{FLOPs} = 2I_iO_i,$$

where I_i and O_i are the input and output dimension of the ith layer, respectively. Thus, the number of FLOPs required for the proposed EE-CSL algorithm is expressed as follows:

$$\begin{aligned}\text{FLOPs} &= 2\left(\sum_{i=1}^{3} I_iO_i + \sum_{i=1}^{4} I_iO_i\right)\\ &= 2\left(U/(K+1)n_1 + n_1^2 + U/(K+1)n_2 + n_2^2\right),\end{aligned}$$

where n_1 and n_2 are the number of neurons in neural networks X_1 and X_2, respectively.

The time complexity of the MOM algorithm is computed as follows: BS has to search all K subchannels for U/2 users. Hence, it requires $K!\left[\binom{U}{1} + \binom{U}{2} + \ldots + \binom{U}{L}\right]$ combinations. The time complexity of the MOM algorithm can be expressed as follows: $O(K!2^{U/2})$. An ES method considers all possible solutions for subchannel allocation. Hence, the time complexity of an ES algorithm is expressed as $O(K!2^U)$.Thus, the complexity of the proposed EE-CSL algorithm for the subchannel assignment of the MIMO-NOMA system is lower than that of other matching algorithms.

4 | SIMULATION RESULTS

In this section, we present the simulation results to demonstrate the performance of the proposed EE-CSL algorithm by optimizing EE in the MIMO-NOMA system. To prove the effectiveness of the proposed EE-CSL algorithm, the performance of ES, a one-to-one matching (OOM) algorithm, and a single-layer network are demonstrated as benchmarks for comparison. An ES algorithm attempted to find an optimal solution by considering all possible subchannel allocation methodologies. To illustrate the significant benefits achieved by the NOMA scheme, the performance of conventional orthogonal multiple access (OMA) for a MIMO-NOMA-based downlink system was also provided. The ES and OOM algorithms were also applied to OMA. It is also inferred that the MIMO-NOMA scheme always outperforms the MIMO-OMA scheme. The specific values of the simulation parameters and parameters used in the co-training-based learning scheme are summarized in Tables 1 and 2, respectively.

Figure 3 illustrates the CDF of the sum rate in the MIMO-NOMA system for three different schemes. The result is evaluated for 7000 random test points. As shown in the figure, the range of the sum rate of the MIMO-NOMA system under different algorithms is mostly distributed between 2×10^9 and 5×10^9. Evidently, the proposed EE-CSL-based subchannel allocation yields better performance than a single-layer DNN. Note that the proposed EE-CSL scheme has close performance to the MOM algorithm and can address the subchannel allocation problem well.

TABLE 1 System parameters.

Parameters	Values
Number of transmit antennas	3
Number of receive antennas	3
Channel bandwidth	10 MHz
Path loss exponent	2.4
Fading	Rayleigh
Noise power spectral density	−174 dBm/Hz

TABLE 2 List of parameters used in the co-training-based learning scheme.

Parameters	Neural network X_1	Neural network X_2
Number of hidden layers	3	4
Batch size	200	500
Learning rate	0.01	0.05
Number of neurons	600	80
Dropout coefficients	0.8	1
Number of training sets	7000	
Number of testing sets	1000	

Figure 4 depicts the convergence of EE in MIMO-NOMA systems. EE is evaluated for different numbers of training data sequences. As shown in the figure, the proposed EE-CSL subchannel allocation scheme converges to 5.33×10^{12} bits/joule during training.

Figure 5 shows the total sum rate of the MIMO-NOMA system versus the number of clusters. As shown in the figure, the sum rate increases with the number of MIMO-NOMA clusters. Evidently, the proposed EE-CSL algorithm outperforms a single-layer neural network. The ES algorithm shows better performance in terms of the total sum rate than other matching algorithms, but involves time complexity. The sum rate performance of the MOM matching algorithm and for a perfectly trained

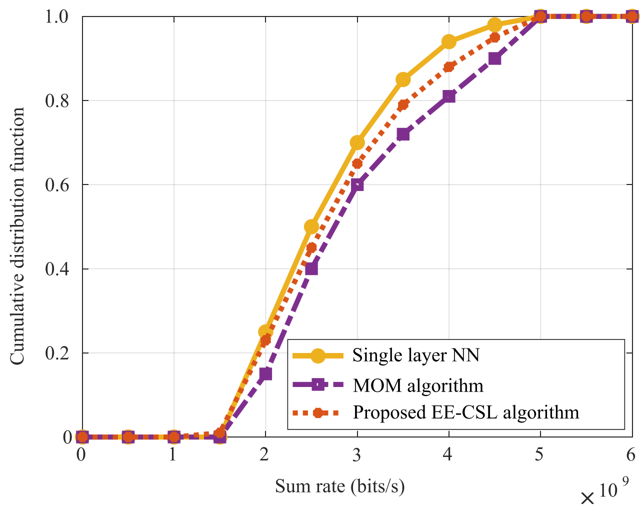

FIGURE 3 CDF that represents the sum rate of MIMO-NOMA systems realized by different algorithms.

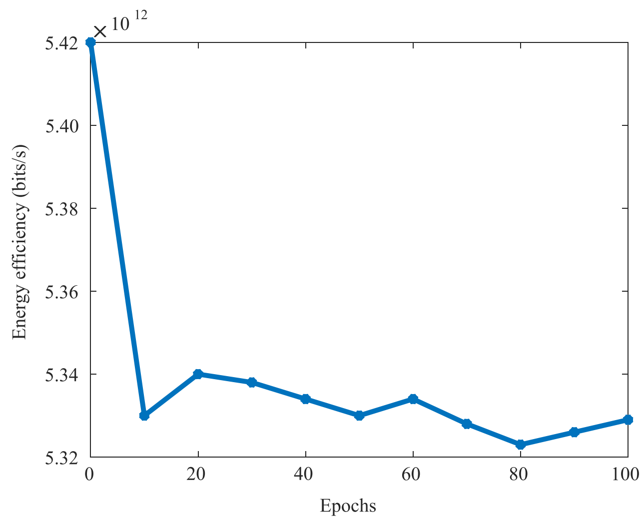

FIGURE 4 Energy efficiency of the semi-supervised learning-based subchannel allocation algorithm (EE-CSL) versus the number of training examples.

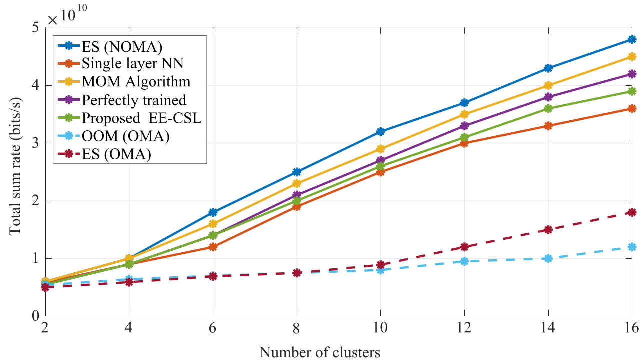

FIGURE 5 Total sum rate versus the number of clusters for different subchannel allocation algorithms.

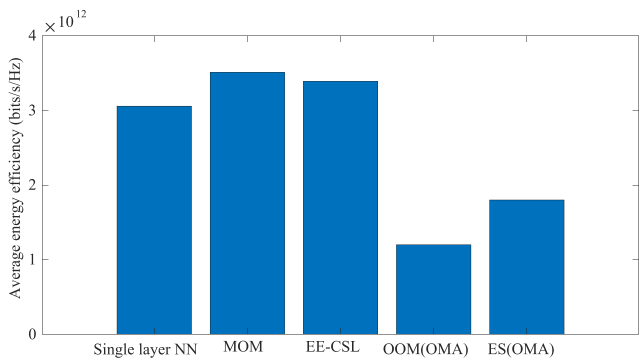

FIGURE 6 Average energy efficiency performance comparison of different subchannel allocation algorithms.

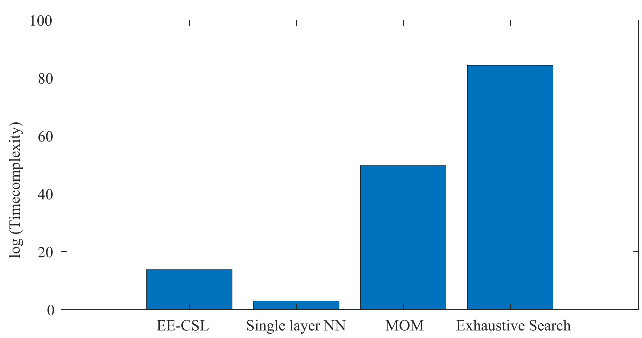

FIGURE 7 Computational complexity comparison of different subchannel allocation algorithms.

case were provided for comparison. In the MOM matching algorithm, matching was performed based on the maximum value of the utility factor, and hence, the algorithm shows better performance. Figure 5 also illustrates the sum rate performance of the MIMO-NOMA scheme. ES and OOM-based OMA were also performed for comparison. As shown in the figure, MIMO-NOMA achieves a larger sum rate than conventional MIMO-OMA due to its high spectral efficiency.

As the formulated optimization problem was designed to maximize the EE of the system, the average EE was computed for different algorithms. Figure 6 depicts a more intuitive comparison of the average EE for different subchannel assignment schemes. The ES method of subchannel allocation shows better EE performance, but involves a higher time complexity. The MOM algorithm also provides better performance because the preference list is created in a decreasing order of the sum rate of the MIMO cluster. The semi-supervised learning method of subchannel allocation has significant EE improvement over a single-layer NN. Comparing the performance of the proposed algorithm with conventional OMA, NOMA offers significant EE improvement.

Figure 7 depicts the performance of different subchannel allocation algorithms of MIMO-NOMA systems in terms of computational complexity. This simulation was performed for 100 users, with two users in a cluster, which requires a total of 50 subchannels. As shown in the figure, the proposed EE-CSL algorithm has a lower computational complexity than other matching algorithms. Although a single-layer NN has the lowest computational complexity among all algorithms, it exhibits poor performance than the proposed EE-CSL algorithm in terms of sum rate and average EE.

5 | CONCLUSION

RA plays a central role in determining the performance of MIMO-NOMA systems. This study mainly considered the problem of subchannel allocation for MIMO-NOMA systems. An energy-efficient ML power optimization problem was formulated under QoS Constraint and was solved using an EE-CSL algorithm. A co-training-based semi-supervised learning algorithm helps improve the learning performance of the system. This scheme also attempts to reduce the dependency of labeled data, and initial data were generated by using the MOM algorithm. Initial assignment using the MOM algorithm improves the EE of the MIMO-NOMA system. Simulation results indicate that the sum rate performance of a co-training-based semi-supervised learning subchannel assignment is closer to the MOM algorithm. Different matching algorithms were considered benchmarks for comparison. The results proved that the proposed EE-CSL algorithm has a lower computational complexity than other matching algorithms. It is also envisioned that the proposed EE-CSL subchannel assignment framework of the MIMO-NOMA system outperforms conventional OMA in terms of sum rate and average EE. The effectiveness of the proposed learning scheme is evident from the performance improvement of MIMO-NOMA systems. Extending the aforementioned subchannel assignment for UAV communications can be the subject of future research.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

ORCID

S. Devipriya https://orcid.org/0000-0003-4954-8088

REFERENCES

1. Z. Ding, Y. Liu, J. Choi, Q. Sun, M. Elkashlan, I. Chih-Lin, and H. Vincent Poor, *Application of non-orthogonal multiple access in LTE and 5G networks*, IEEE Commun. Mag. **55** (2017), no. 2, 185–191.
2. 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*, JSAC. **35** (2017), no. 10, 2181–2195.
3. Y. Tao, L. Liu, S. Liu, and Z. Zhang, *A survey: Several technologies of non-orthogonal transmission for 5G*, China Commun. **12** (2015), no. 10, 1–15.
4. Y. Wang, B. Ren, S. Sun, S. Kang, and X. Yue, *Analysis of non-orthogonal multiple access for 5G*, China Commun. **13** (2016), no. Supplement2, 52–66.
5. O. Maraqa, A. S. Rajasekaran, S. Al-Ahmadi, H. Yanikomeroglu, and S. M. Sait, *A survey of rate-optimal power domain NOMA with enabling technologies of future wireless networks*, IEEE Commun. Surv. Tutor. **22** (2020), no. 4, 2192–2235.
6. B. Makki, K. Chitti, A. Behravan, and M. -S. Alouini, *A survey of NOMA: Current status and open research challenges*, OJ-Coms. **1** (2020), 179–189.
7. D. Wan, M. Wen, X. Cheng, S. Mumtaz, and M. Guizani, *A promising non-orthogonal multiple access based networking architecture: Motivation, conception, and evolution*, IEEE Wirel. Commun. **26** (2019), no. 5, 152–159.
8. D. Wan, R. Huang, M. Wen, G. Chen, F. Ji, and J. Li, *A simple multicarrier transmission technique combining transmit diversity and data multiplexing for non-orthogonal multiple access*, IEEE Trans. Veh. Technol. **70** (2021), no. 7, 7216–7220.
9. D. Wan, M. Wen, F. Ji, Y. Liu, and Y. Huang, *Cooperative NOMA systems with partial channel state information over nakagami- m fading channels*, IEEE Trans. Commun. **66** (2018), no. 3, 947–958.
10. X. Liu, Y. Liu, X. Wang, and H. Lin, *Highly efficient 3-D resource allocation techniques in 5G for NOMA-enabled massive MIMO and relaying systems*, J-Sac. **35** (2017), no. 12, 2785–2797.
11. M. Zeng, A. Yadav, O. A. Dobre, and H. V. Poor, *Energy-efficient power allocation for MIMO-NOMA with multiple users in a cluster*, IEEE Access. **6** (2018), 5170–5181.
12. X. Zhang, X. Zhu, and H. Zhu, *Joint user clustering and multi-dimensional resource allocation in downlink MIMO–NOMA networks*, IEEE Access. **7** (2019), 81783–81793.
13. P. Liu, Y. Li, W. Cheng, W. Zhang, and X. Gao, *Energy-efficient power allocation for millimeter wave beamspace MIMO-NOMA systems*, IEEE Access. **7** (2019), 114582–114592.
14. F. Fang, J. Cheng, and Z. Ding, *Joint energy efficient subchannel and power pptimization for a downlink NOMA heterogeneous network*, IEEE Trans. Veh. Technol. **68** (2019), no. 2, 1351–1364.
15. J. Wang, H. Xu, L. Fan, B. Zhu, and A. Zhou, *Energy-efficient joint power and bandwidth allocation for NOMA systems*, IEEE Commun. Lett. **22** (2018), no. 4, 780–783.
16. B. Di, L. Song, and Y. Li, *Sub-Channel assignment, power allocation, and user scheduling for non-orthogonal multiple access etworks*, IEEE Trans. Wirel. Commun. **15** (2016), no. 11, 7686–7698.
17. Q. Wang and F. Zhao, *Joint spectrum and power allocation for NOMA enhanced relaying networks*, IEEE Access. **7** (2019), 27008–27016.
18. X. Li, C. Li, and Y. Jin, *Dynamic resource allocation for transmit power minimization in OFDM-based NOMA systems*, IEEE Commun. Lett. **20** (2016), no. 12, 2558–2561.
19. H. Zhang, B. Wang, C. Jiang, K. Long, A. Nallanathan, V. C. M. Leung, and H. V. Poor, *Energy efficient dynamic resource optimization in NOMA system*, IEEE Trans. Wirel. Commun. **17** (2018), no. 9, 5671–5683.
20. J. Shi, W. Yu, Q. Ni, W. Liang, Z. Li, and P. Xiao, *Energy efficient resource allocation in hybrid non-orthogonal multiple access systems*, IEEE Trans. Commun. **67** (2019), no. 5, 3496–3511.
21. J. Zhao, Y. Liu, K. K. Chai, Y. Chen, and M. Elkashlan, *Joint subchannel and power allocation for NOMA enhanced D2D communications*, IEEE Trans. Commun. **65** (2017), no. 11, 5081–5094.
22. M. Liu, T. Song, and G. Gui, *Deep cognitive perspective: Resource allocation for NOMA-based heterogeneous IoT with imperfect SIC*, IEEE Internet Things J. **6** (2019), no. 2, 2885–2894.
23. H. Huang, Y. Yang, Z. Ding, H. Wang, H. Sari, and F. Adachi, *Deep learning-based sum data rate and energy efficiency optimization for MIMO-NOMA systems*, IEEE Trans. Wirel. Commun. **19** (2020), no. 8, 5373–5388.
24. L. Sanguinetti, A. Zappone, and M. Debbah, *Deep learning power allocation in massive MIMO*, (52nd Asilomar conference on signals, systems, and computers, Pacific Grove, CA, USA), 2018, 1257–1261.
25. G. Gui, H. Huang, Y. Song, and H. Sari, *Deep learning for an effective nonorthogonal multiple access scheme*, IEEE Trans. Veh. Technol. **67** (2018), no. 9, 8440–8450.
26. H. Zhang, M. Feng, K. Long, G. K. Karagiannidis, and A. Nallanathan, *Artificial intelligence-based resource allocation in ultradense networks: Applying event-triggered Q-learning algorithms*, IEEE Veh. Technol. Mag. **14** (2019), no. 4, 56–63.
27. Y. Cao, G. Zhang, G. Li, and J. Zhang, *A deep Q-network based-resource allocation scheme for massive MIMO-NOMA*, IEEE Commun. Lett. (2021), 3055348.
28. H. Zhang, H. Zhang, K. Long, and G. K. Karagiannidis, *Deep learning based radio resource management in NOMA networks: User association, subchannel and power allocation*, IEEE Trans.Netw. Sci. Eng. **7** (2020), no. 4, 2406–2415.
29. H. Zhang, D. Zhang, W. Meng, and C. Li, *User pairing algorithm with SIC in non orthogonal multiple access system*, (IEEE Int. Conf. Communications, Kuala Lumpur, Malaysia), 2016, pp. 1–6. https://doi.org/10.1109/ICC.2016.7511620

30. Z. Zhou and M. Li, *Semisupervised regression with cotraining-style algorithms*, IEEE Trans. Knowl. Data Eng. **19** (2007), no. 11, 1479–1493.
31. Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, *Matching theory for future wireless networks: Fundamentals and applications*, IEEE Commun. Mag. **53** (2015), no. 5, 52–59.
32. I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*, The MIT Press, 2016.

AUTHOR BIOGRAPHIES

S. Devipriya received her BE degree in Electronics and Communication Engineering from Periyar Maniammai University in 2012 and the ME degree in Communication Systems from SSN College of Engineering, Chennai, in 2014. She is currently pursuing the PhD degree in Information and Communication Engineering at Anna University, Chennai, India. Since 2014, she has been an Assistant Professor with the Department of Electronics and Communication Engineering, St.Joseph's College of Engineering, Chennai, India. Her research interests include cooperative communication, signal estimation, deep learning, resource allocation in wireless communication, and UAV communications.

J. Martin Leo Manickam is working as Professor in the Department Electronics and Communication Engineering at St. Joseph's College of Engineering, Chennai. He acquired BE degree in Electronics and Communication Engineering from Alagappa Chettiar College of Engineering and Technology, Karaikkudi in 1995. He received ME degree in Optical Communication and PhD degree in the Faculty of Information and Communication Engineering from the College of Engineering, Anna University, Chennai. He has over 24 years of experience in teaching and guiding projects for Undergraduate and post graduate students. Under his guidance, 11 scholars had got PhD degree and six research scholars are pursuing their PhD program. He has to his credit 80 publications in National/International conferences and journals. His areas of interest include mobile ad hoc networks, wireless sensor networks, cognitive radio, digital communication and network security. He is a fellow in IEI and IETE.

B. Victoria Jancee graduated from Bharathiar University, Coimbatore in Electronics and Communication Engineering during the year 1992. She obtained her Master degree in Applied Electronics from Sathyabama University, Chennai, during the year 2004. She has obtained her PhD from Faculty of Information & Communication Engineering, Anna University, Chennai, in the year 2015. At present, she is working as Associate Professor in the Department of ECE, St. Joseph's College of Engineering, Chennai. She got a total teaching experience of over 28 years in engineering colleges. She is the life member of ISTE. She has eight publications in International and National Journals and conferences in the area of Wireless Sensor Networks. Her area of research is decision fusion in wireless sensor networks, decentralized sequential detection, and fault-tolerant event detection in wireless sensor networks.

How to cite this article: S. Devipriya, J. Martin Leo Manickam, and B. Victoria Jancee, *Energy-efficient semi-supervised learning framework for subchannel allocation in non-orthogonal multiple access systems*, ETRI Journal **45** (2023), 963–973. DOI 10.4218/etrij.2022-0251