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Deep Learning (DL) Based Joint Resource Allocation and RRH Association in 5G-Multi-Tier Networks

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ABSTRACT Fifth-Generation (5G) networks have adopted a multi-tier structural model which includes femtocells, picocells, and macrocells to ensure the user quality-of-service (QoS). To meet these QoS demands, the system requires optimization of different resources in different network dynamics carefully. However, if ignored, this will lead to long processing delays and high computational burdens. To avoid this, we proposed Deep Learning (DL) based resource allocation (RA) as a promising solution to meet the network requirements. DL is an effective mechanism where neural networks can learn to develop RA techniques. Thus, an optimized RA decision can be achieved using DL without exhaustive computations. Further, DL uses DL to achieve solutions for joint RA and remote-radio-head (RRH) association problems in multi-tier Cloud-Radio Access Networks (C-RAN). Initially, a summary of existing literature on DL-based RA techniques is provided, followed by a deep neural network (DNN) description, its architectures, and the data training method. Then, a supervised DL technique is presented to solve the joint RA and RRH-association problem. An efficient subchannel assignment, power allocation, and RRH-association (SAPARA) technique are used to generate the training data for the DNN model using the iterative approach where the seed data for the SAPARA technique is taken using a uniform power allocation and path-loss based association (UPA-PLBA) model. After training the DNN model, the accurateness of the presented model is tested. Simulation outcomes demonstrate that our proposed scheme is capable of providing an efficient solution in the considered scenario.

INDEX TERMS Deep learning, resource allocation, RRH-association, multi-tier networks, cloud-radio access networks, 5G networks.

I. INTRODUCTION

To day Internet of Things (IoT) and the 5th-Generation (5G) cellular networks are envisioned to handle numerous evolving applications and integrated devises which demand high Quality-of-Service (QoS) with low latency rate [1], [2]. To ensure the QoS demands of various types of applications, many resource allocations (RA) techniques have been developed which maximize network sum-rate, energy-efficiency (EE), or spectrum efficiency [3], [4]. However, in practical 5G cellular networks, two main challenges are countered while applying existing RA optimization techniques. First, QoS limitations of some services, such as low-latency, ultra-reliable, and delay-sensitive services, may lack closed-form representation. To implement RA optimization techniques, the QoS achieved by a certain policy needs to be evaluated by the system via extensive simulations, and consequently suffers from a high processing burden [5]. Next, even if the closed-form representation is achievable in certain cases, the problems are generally non-convex [4], [5]. The system also requires RA updating through these non-convex problems that result in a high computational burden.

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Even for some convex optimization problems solvable by certain efficient techniques, e.g., interior-point algorithm (IPA), the computational burden is still very high for real time deployment [6]. Deep learning (DL) is a capable methodology [7] to perform real time optimal RA [8]–[10]. The main objective is to deploy a Neural Network (NN) to estimate the RA strategy that maps states of the systems to the optimal RA. To this end, the system initially trains the NN offline through a huge number of labeled data samples. Then for any specified input, the optimal RA can be achieved from the network output. As the theory of universal approximation stated that if the optimal policy is a continuous function and deterministic, then, as the neurons number tends to infinity, the approximation errors tend to zero [11]. It should be clear that the use of DL in wireless systems is not a simple task. Performing the optimization of certain variables, e.g., antennas count, subchannels, and user-association, the NN estimation can be incorrect owing to the variable's quantization. Consequently, the achieved NN results cannot completely ensure the QoS. Furthermore, labeled training samples will be required in large number by the DL model. To attain labeled training samples, an optimization technique should be designed first for the optimization problem solution. Even if training samples are achieved in large numbers, the trained NN is not precise due to the dynamic nature of the wireless system. Such as, the service types and channel itself in the system may change with time. These varying parameters which are not contained within the NN inputs are called hidden variables [12]. While training the model, hidden variables are supposed to be fixed, but, practically, they drift over time. The authors in [12] showed that hidden variables could be malicious in the DL model.

A. RELATED WORK

Researchers have broadly considered efficient RA. The authors in [13] considered QoS as the objective and jointly optimized the RA and antenna configuration in multi-tier cellular systems. Effective capacity was implemented for resource optimization techniques in [14], [15] to ensure the queuing delay bound. In low-latency and ultra-reliable communications, to decrease transmission delay, the basic relation of probability decoding error to block-length was formulated in [16]. The relation in [16] was utilized for RA optimization in low-latency and ultra-reliable communications [4], [17]. The QoS limitations lack closed-form representation for many of these works, and the RA technique will not be implementable in real-time. Estimating RA strategies with NNs are studied in [8], [18]. It is shown in [7] that a power control technique in multi-tier systems can be correctly estimated through fully connected NN. In [10] and [18], convolutional NN are implemented to approximate content delivery and power control policies, respectively. To enhance EE, [14] presented an online DL model for the EE and power control approximation technique acquired from the fractional-programming model [19]. Due to the unavailability of an optimum RA optimization technique, unsupervised DL was implemented in [20], where the NN parameters are trained to fulfill the Karush-Kuhn-Tucker optimization conditions. However, the Karush-Kuhn-Tucker conditions do not exist when integer variables are not specified for a close set. Considering the highly dynamic nature of wireless networks, NNs trained off-line are unable to attain the required performance in varying networks. To deal with this problem, deep transfer learning was implemented by some researchers. Such as, when the traffic patterns [22], data-arrival processes [21], or the network size [23] vary, deep transfer learning could be implemented in order to fine-tune the NNs.

B. CONTRIBUTION

With the DL model for RA in an outsized cellular system, a multi-tier NN mechanism can be established to which the appropriate input training samples can be given, and then the RA solution can be acquired as outputs without exhaustive computations [3]. Moreover, the introduction of cloud storage technologies made it possible to handle the training of the DL model as well as the computation, analysis, and storage of big data. This paper studies the use of DL for RA in multi-tier cellular systems. Initially, a summary of existing literature on DL based RA techniques is provided. Then, a NN, its architectures, and the data training method are briefly discussed. Furthermore, a supervised DL technique is presented to solve the joint RA and RRH-association problem. An efficient Power allocation, subchannel assignment, and RRH-association (SAPARA) technique are used to generate the training data for the DNN model using the iterative approach where the seed data for the SAPARA technique is taken using uniform power allocation and path-loss based association (UPA-PLBA) model. After training the DNN model, the performance of the presented model in estimating the RA solutions is tested.

C. PAPER STRUCTURE

The remaining sections are structured as follows. Sections II and III contain a brief overview of a DNN and the considered system model, respectively. Section IV includes the proposed supervised DL technique. Section V is about simulated results, while Section VI concludes the paper.

II. AN OVERVIEW OF DEEP LEARNING

DL is a multi-layered feed-forward technique that is used to build and train NNs. A basic DL technique allows the transformation of input data and feature extraction. In the following subsections, first, a deep neural network (DNN) is briefly discussed, and then the architecture of relevant DNN is presented, followed by its data training method.

A. DEEP NEURAL NETWORK

A DNN consists of three layers: input, output, and hidden layers, as shown in Figure 1. Each layer contains multiple elements called neurons which perform a non-linear process on the input data. First, calculation of the input weights summation is performed followed by the addition of a bias

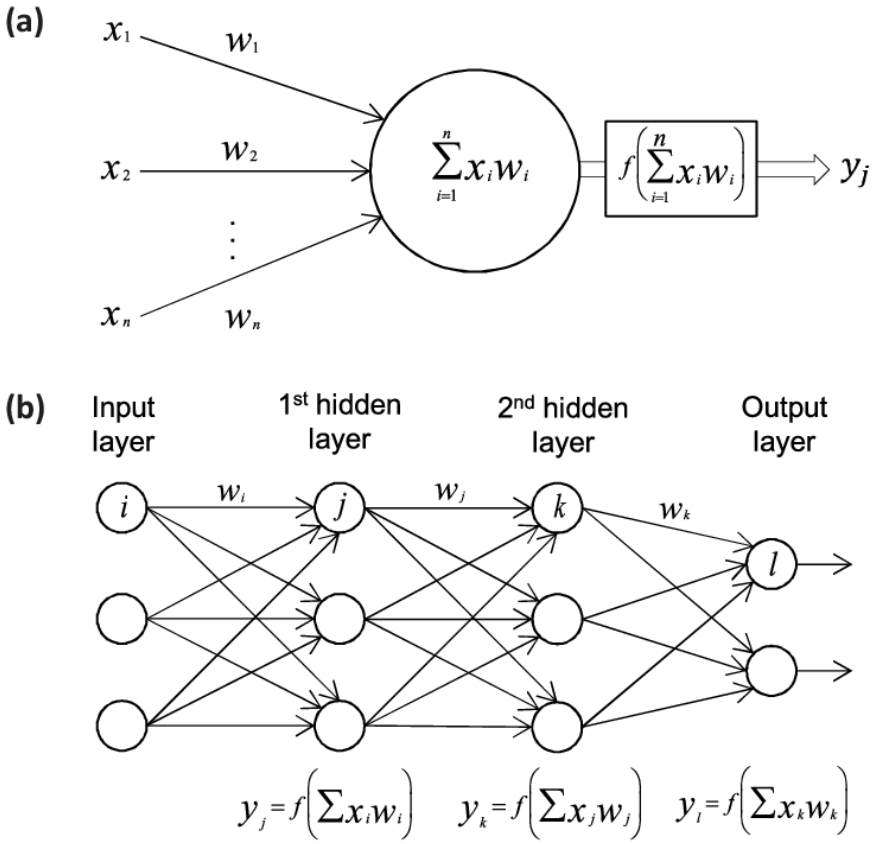

FIGURE 1. Illustration of a Deep Neural Network (DNN).

value to this sum before becoming the input of an activation function, such as Sigmoid function given as below

$$\varphi(x) = 1/1 + e^x \tag{1}$$

where x represents the input. The purpose of the activation function is to set a non-linear input-output association [1]. Figure 1 shows the illustration of a single neuron that contains two vectors: weight and bias. If x represents the input of i-th hidden layer, its output is then $h^i = \varphi^i(w^i x + b^i)$, where φ^i, (w^i and b^i) represent the activation function, the weight vector, and the bias vector of i-th hidden layer, respectively.

B. DEEP LEARNING ARCHITECTURE

DL takes advantage of the convolutional NNs, unsupervised pre-trained NNs, recursive NNs, and recurrent NNs architectures. The DL model can be implemented with three models: unsupervised learning, supervised learning and reinforcement learning. In an unsupervised model, due to the absence of a supervisor, the data set does not have a pre-defined outcome; therefore, the main objective is to assume the outputs appropriately for a specific unlabeled input dataset. In supervised learning, a supervisor assists the model in learning the features from the given dataset. Therefore, for each input, the dataset provides the target. Supervised learning is suitable for regression and classification problems. In reinforcement learning, a software agent is there that interacts with the environment for learning. The agent decides an action after sensing its existing state and the state of the environment. There is a possible result of every move, i.e., the agent either gets a reward or penalty for a right move or bad move, respectively. The agent's main responsibility is cumulative reward maximization. This paper emphasizes a type of unsupervised pre-trained NNs [4] named Auto-Encoder (AE), which reproduces the inputs at the outputs. This way, the unlabeled dataset feature space is leaned by the AE. It generally involves three types of layers, i.e., input, output, and hidden layers. The neurons should be the same in number at both the input and output layers. AE involves an encoder, a decoder that performs input data to a hidden code conversion, and hidden code to input conversion. AE has various types: stacked AE, denoising AE, variational AE, and sparse AE [5].

C. DATA TRAINING PROCEDURE

Suppose that we have to learn y where y is a target function expressed by $y = f^*(x)$. Here, x and y are the input and output vectors, respectively. Thus, the DL model is represented by $y = f(x; q)$, where q represents weights and biases. The main objective is to accurately learn q so that the presented and original models can be closed in performance. For this purpose, various techniques (e.g., Momentum, Stochastic Gradient, AdaGrad, Adam, and RMSProp)

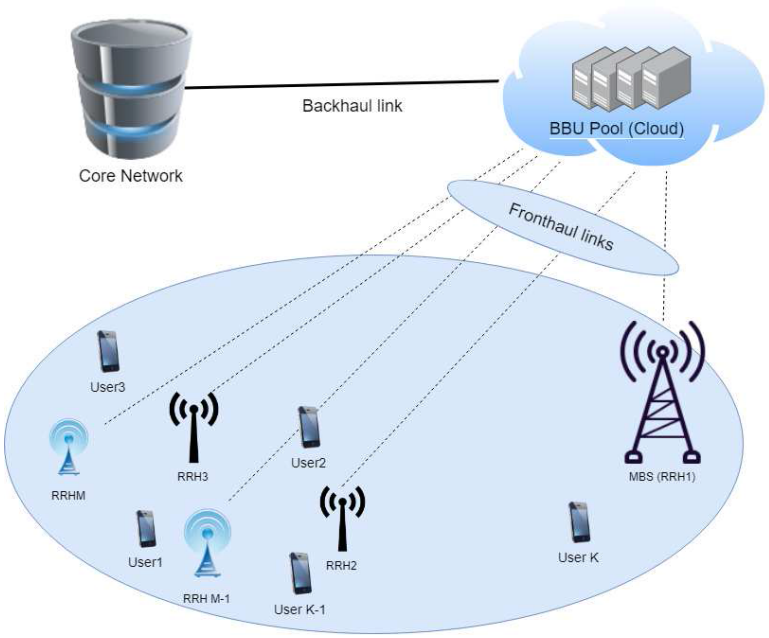

FIGURE 2. Illustration of multi-tier C-RAN.

can be implemented [24]. A dataset comprised of inputs values and outputs values are used for the training of the model. To this end, first, the weights and biases are arbitrarily initialized and then fed to the input layer, whereas the output from this layer is provided to the hidden layer as an input. Furthermore, a cost function is implemented to find the model quality by computing the error between the target value and the predicted value. Then the backward pass is performed where the following error is transmitted backward to updates the values of weights and biases at every layer. This training lasts until the error rate approaches a threshold value. One complete round of a forward pass and backward pass is known as an epoch or a training cycle. A maximum number can be set for training cycles upon reaching which the training practice can be ended. Such a NN is called a feed-forward, and back-propagation NN is utilized in our presented DL model.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

The UL of a SC-FDMA-based multi-tier 5G C-RAN is considered a total of 3 communication tiers, as shown in Figure 2. A three-tier infrastructure is divided as follow, tier 1 is served by microcell, tier 2 is looked by picocell-RRHs, while tier 3 is cared by femtocell-RRHs. In additions, we have total of M RRHs including three tier RRHs. Also, $(M-1)/2$ femtocell-RRHs and the same number of picocell-RRHs are underlaid in the microcell. Our presented multi-tier C-RAN consists of a BBU pool, a group of RRHs, cloud and core network. The first two are interconnected through fronthaul links, and the last two are connected through a backhaul link. In present infrastructure MBS-RRH and small cell RRHs are responsible for transmitting control signal to C-RAN and data transmission respectively. Moreover, SC-FDMA is considered a UL multiple access techniques in our presented multi-tier C-RAN.

TABLE 1. List of symbols.

Symbols	Description
M	Total number of RRHs
N	Total number of sub-channels
K	Total number of users
$p_{k,n}$	Transmit power of kth user on nth sub-channel
p_k^{max}	Maximum per user transmit power
$\alpha_{k,m}$	User association of user k with RRH m
$\gamma_{k,n}^m$	SNIR of kth user on nth sub-channel to RRH m
$\lvert h_{k,n}^m \rvert^2$	Channel gain of kth user on nth sub-channel to RRH m
$I_{k,n}^m$	Interference on nth sub-channel of kth user to RRH m
$p_{l,n}$	Transmit power of the lth user on nth sub-channel
$\lvert h_{l,n}^m \rvert^2$	Channel gains of the lth user on nth sub-channel to RRH m
σ^2	Noise
$R_{k,n}^m$	Network sum-rate

In addition, we assumed total K randomly deployed users. Based on this total bandwidth is orthogonally sub-divided into N sub-channels. Each RRH reuses the available set of all sub-channels independently of all other RRHs in the system. As all the RRHs share the same set of sub-channels, the associated users of different RRHs transmit on the same channel, resulting in interference. The sub-channel adjacency and exclusivity constraints of SC-FDMA ought to be fulfilled, wherein only an adjacent couple of sub-channels can be assigned to a user. A sub-channel can be assigned to one user at a time respectively. Different symbols used in this chapter and their description are listed in Table 1.

It is anticipated that a user can be linked to only one RRH and a user could be allotted several subchannels if

$$\sum_{n\epsilon N_k^m} p_{k,n} \leq p_k^{max}, \ \ \forall k, p_{k,n} \geq 0 \ \ \forall k, n, \tag{2}$$

where N_k^m, $p_{k,n}$ and P_k^{max} indicate the subchannels of user k linked to m-th RRH, the power transmitted by k-th user on n-th subchannel and the maximum transmit power of k-th user, respectively. The subchannel exclusivity and adjacency restrictions are satisfied. The full channel information availability to every user is also considered.

Let $|h_{k,n}^m|^2$ and $I_{k,n}^m$ be gain of the channel, and interference, respectively, of k-th user to m-th RRH on n-th subchannel, and σ^2 be the noise. Then, SINR on n-th subchannel from user k to m-th RRH, is shown as follows:

$$\gamma_{k,n}^m = \frac{p_{k,n}|h_{k,n}^m|^2}{\sigma^2 + I_{k,n}^m}, \tag{3}$$

where

$$I_{k,n}^m = \sum_{l \neq k} p_{l,n}|h_{l,n}^m|^2 \tag{4}$$

The k-th user possible data-rate is denoted as follows:

$$R_{k,n}^m = W|N_k^m| \log_2 \left(1 + \frac{1}{|N_k^m|} \sum_{n\epsilon N_k} (\gamma_{k,n}^m)\right) \tag{5}$$

The EE is designated as the transmitted bits per unit energy consumption at the source side, which is shown as follows:

$$\eta_k^m = \frac{R_k^m}{P_T^k} \tag{6}$$

where P_T^k shows the energy consumption of user k and comprises of two quantities: the collective transmit powers on all its subchannels $\sum_{n\epsilon N_k^m} p_{k,n}$ and the static and dynamic circuit energy consumption of k-th user represented by P_k^s and εR_k^m, respectively. P_T^k can be represented as follows:

$$p_T^k = \sum_{n\epsilon N_k^m} p_{k,n} p_k^s + \varepsilon R_k^m \tag{7}$$

where ξ and ε show the reciprocal of the power amplifier's drain efficiency and dynamic power consumption per unit data rate, respectively [6].

Besides, the matrix for RRH-association is molded as $\alpha_{k,m}$) where

$$\alpha_{k,m} = \begin{cases} 1, & \text{if a user is connected to RRH } m \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

and the optimization problem is formulated as follows

$$\max \sum_{m=1}^{M} \sum_{k=1}^{K} \alpha_{k,m} \eta_k^m \tag{9}$$

$$s.t. \ C1 : \sum_{n\epsilon N_k^m} p_{k,n} \leq p_k^{max}, \ \ \forall k, p_{k,n} \geq 0, \ \forall k, n \tag{10}$$

$$C2 : \sum_{m=1}^{M} \alpha_{k,m} = 1, \ \ \forall k, \alpha_{k,m} \epsilon \{0, 1\}, \ \forall k, m \tag{11}$$

$$C3 : N_k^m \cap N_j^m = \emptyset, \ \ \forall k \neq j, \ \forall m \tag{12}$$

$$C4 : \left\{ n \cap \left(\bigcup_{j=1, j\neq k}^{k} N_j^m \right) = \emptyset | \right.$$
$$\left. n\epsilon \{n_1, n_1 + 1, \ldots, n_2 - 1, n_2\} \right\}, \ \ \forall k, m \tag{13}$$

$$C5 : \sum_{m=1}^{M} \alpha_{k,m} R_k^m \geq R_k^{min}, \ \ \forall k \tag{14}$$

where $n_1 = min(N_k^m)$, $n_2 = max(N_k^m)$ and R_k^{min} indicates the minimum rate condition of k-th user. Objective function is represented in Equation (9). Equations (10) and (11) indicate transmit power bounds and RRH association restrictions of a user, respectively. Two Equations (13) and (12) showing subchannel exclusiveness and adjacency restrictions, respectively. Equation (14) showing minimum rate condition of k-th user.

IV. A SUPERVISED DEEP LEARNING TECHNIQUE FOR RA AND RRH-ASSOCIATION IN A MULTI-TIER NETWORK

We propose a DL technique that can predict optimal joint RA and RRH-association solutions in a multi-tier C-RAN. Mainly, this DL technique takes the $K, N, M, and\ p^{max}$ as input and guesses the power and sub-channel assignments and RRH-association as output. The technique continues in the following stages.

A. DATA GENERATION

To achieve the optimal solution for joint RA and RRH-association problem, a mixed integer non-liner programming (MINLP) problem, one approach is to perform the exhaustive search. The subchannel adjacency constraints in Equations (12) and (13) imposed by the SC-FDMA lead to vast search space, e.g., even for a secure power allocation and RRH-association, the optimal subchannel assignment lonely is extremely hard. For example, if there are 24 subchannels and 10 users, then for a fixed power allocation and RRH-association, a search across $5.26 * 10^{12}$ subchannels assignments will be required to achieve the optimal result, which indicates that the solution of (9) to (14) is extremely hard and time consuming through exhaustive search method. Therefore, the three stages iterative SAPARA technique [3] is used for training and test data generation for our presented DNN model.

B. JOINT SAPARA ALGORITHM

Our presented joint SAPARA algorithm is provided in Algorithm 1, while its step by step explanation is given below.

Step 1: To provide the initial input data for SAPARA algorithm, we supposed the initial RRH-association vector and power allocation vector as $\boldsymbol{\alpha^0}$ and $\boldsymbol{p^0}$, respectively, such that $\boldsymbol{\alpha^0} = \alpha_1^0.\alpha_2^0, \ldots\ldots \alpha_k^0$ and $p_{,n}^0 = p_k^{max}/|N_k^m|, \forall k, n, m$. We perform initialization by UPA-PLA algorithm where

Algorithm 1 SAPARA Algorithm

1: **Initialization** $K;\ N;\ M;\ \widetilde{K} = \{1, \ldots, K\};$
2: $\widetilde{N^m} = \{1, \ldots, N\};\ \widetilde{M} = \{1, \ldots, M\};\ N_k^m = \phi,\ \forall\, k \epsilon \widetilde{K},$
3: $\forall m \epsilon \widetilde{M};\ N_k^{m,f} = \widetilde{N^m},\ \forall k \epsilon \widetilde{K};\ R_k^{min},\ \forall k;\ R_k^m = 0, \forall k,\ m$
4: **while** $\widetilde{M} \neq \phi$ **do**
5: **while** $\widetilde{N^m} \neq \phi$ **do**
6: $\forall\, k \epsilon \widetilde{K_m}$
7: $\forall\, n \epsilon N_k^{m,f} \ \cup\ \widetilde{N}$
8: $\eta_k^m = f(\eta_k),\ N_k^m \cup n$
9: $k^*,\ n^* = \arg\ \max_{k,n}\ \eta_k^m$
10: $N_{k^*}^m = N_{k^*}^m \cup n^*$
11: $\widetilde{N^m} \backslash n^*$
12: $N_k^{m,f} = \{\min(N_{k^*}^m) - 1,\ \max(N_{k^*}^m) + 1\} \cap \widetilde{N^m}$
13: $R_{k^*}^m = W\ |N_k^m|\ \log_2\left(1 + \frac{1}{|N_{k^*}^m|} \sum_{n\, \epsilon\, N_{k^*}^m} \left(\frac{p_{k^*,n}\, |h_{k^*,n}^m|^2}{\sigma^2 + I_{k^*,n}^m}\right)\right)$
14: **while** $(R_{k^*}^m < R_{k^*}^{min}\ and\ N_{k^*}^{m,f} \neq \phi)$ **do**
15: $\triangle \eta_{k^*}^m = f(\eta_{k^*}, N_{k^*}^m \cup n) - f(\eta_{k^*}, N_{k^*}^m),\ \forall\, n \epsilon N_{k^*}^{m,f}$
16: $n^* = \arg\ \max_{n\, \epsilon\, N_{k^*}^{m,f}}\ \triangle \eta_{k^*}^m$
17: Repeat steps 10 to 13
18: **end while**
19: $\widetilde{K} \backslash\, k^*$
20: **end while**
21: $\widetilde{M} \backslash\, m$
22: **end while**

$p_{k,n}^0 = p_k^{max}/|N_k^m|, \forall k, n, m$ and $\forall k$: $\alpha_{k,\bar{m}}^0 = 1$ for $\bar{m} = \arg min\, d_{k,m}$; $\alpha_{k,m}^0 = 0, \forall m \neq \bar{m}.\ d_{k,m})$ indicates the distance between m and k. In addition, N_k^m is set to empty, as initially there are no subchannels assigned to user k, therefore, $N_k^m = \phi$, and N_k^{mf} which shows the achievable subchannels set for k-th user connected to m-th RRH is set to has all the subchannels are available initially therefore, $N_k^{mf} = N$.

Step 2: After initialization in the first step, the SAPARA technique picks one RRH, calculates the EE of all its users on each subchannel, and then allots the subchannel to a user based on maximum EE achievement (Lines 8-9). This user-subchannel pair is symbolized by (k^*, n^*). After allotting n^* to k^*, $N_k^{m,f}$, and $N_{k^*}^m$ are updated (Lines 10-12). Line 13 find the possible data rate of user k^* on its updated subchannels set allotted to it. Then, an additional subchannel is allotted to that user from the $N_{k^*}^{m,f}$ till the $R_{k^*}^{min}$ is fulfilled (Lines 14-18). In these lines, primarily the growth in the EE indicated by $\triangle \eta_{k^*}^m$ is found for each extra subchannel such that $n \epsilon N_k^m$ (Line 15), which indicates the difference between the EE of k^* when the subchannel n is added to its allotted subchannels set and its EE without the addition of subchannel n. Line 16 chooses the most advantageous subchannel in terms of EE. In Line 17, the sequences listed in Lines 10-13 are re-performed to update $N_k^{m,f}$, $N_{k^*}^m$, and $R_{k^*}^{min}$. Line 19 updates the set of users without subchannels. The practice is re-performed until M goes empty (Lines 5-21). We named this subchannel assignment as an individual subchannel assignment (ISA) technique given in Table 1.

Step 3: After attaining $N_{k^*}^m$ by carrying out subchannels assignment in the first step and for given $\boldsymbol{\alpha} = \alpha^i, p_{k,n}$ is calculated using IPA [25], which is an efficient solver of linear and non-linear problems.

Step 4: We perform RRH-association using the integer relaxation technique [26]. The suggested technique links k with m, which provides peak EE to k. We symbolize this solution by α^{I+1} and then $(i+1) - th$ iteration starts. The presented technique is re-performed until convergence.

Step 5: Steps 1-4 are repeated until a significant quantity of data is attained to train our DNN model. To end, the pre-trained DNN model is used to forecast joint RA and RRH-association. This forecast will be executed online.

C. TRAINING AND TESTING STAGE

The training dataset contains input data and target data. A stacked AE is used to initiate the biases and weights for the hidden layers. Like so, our model is pre-trained, and then a SoftMax layer is added, which allocates probabilities to every class such that the probability sum must be 1. The AE encoder part is stacked with the SoftMax layer, and the model is fine-tuned with the labeled training dataset. Once the training process is completed, the model is tested on a different dataset, and the model accuracy is calculated. Our considered DNN model is provided in Figure 3.

D. COMPLEXITY OF THE JOINT SAPARA ALGORITHM

To analyze the complexity of our SAPARA Algorithm, the iterations of middle and innermost while loops are considered in SAPARA Algorithm. In Algorithm 1, the section containing these two loops will run for M number of times. This complexity comes from steps 8 and 15 in which η_k^m and $\triangle \eta_{k^*}^m$ are computed. The complete iteration of middle while loop will require $\mathcal{O}(NK)$ operations to compute η_k^m. This complexity reduces due to subsequent iterations as the number of users and sub-channels will be less than K and N, accordingly. Also, the first complete iteration of another loop i.e., innermost while loop requires $\mathcal{O}(|N_k^f|)$ operations to compute $\triangle \eta_{k^*}^m$. However its worst case complexity will be $\mathcal{O}((N-1)|N_k^f|)$. The complexity reduces for the subsequent iterations of innermost while loop as the number of the sub-channels will be less than $(N-1)$. Because there are N middle iterations which will run for M number of times, the worst-case complexity of the algorithm cannot exceed $\mathcal{O}(M(N(NK + (N-1)|N_k^f|)))$.

V. SIMULATED RESULTS

A multi-tier C-RAN is assumed in the UL comprising a macrocell RRH tier with 1000 meters radius, a picocell RRH tier containing two RRHs, and a picocell RRH tier containing two RRHs. Besides, the system's bandwidth is 9 MHz, which is divided equally among the N subchannels.

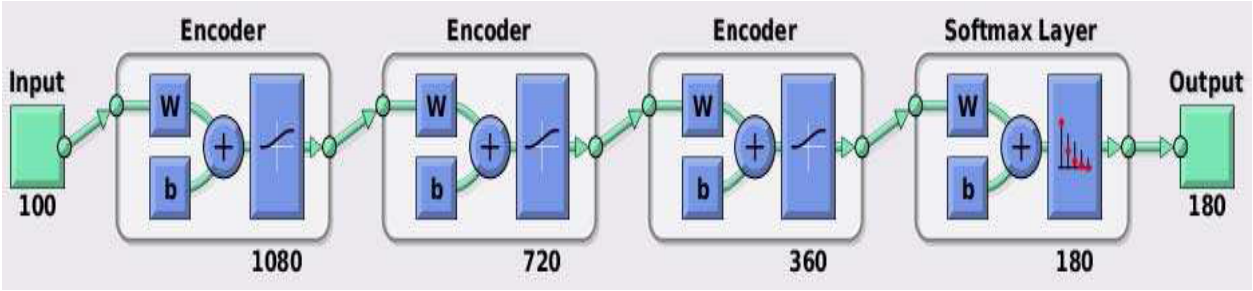

FIGURE 3. Our proposed DNN model.

The bandwidth of every individual sub-channel is 200 kHz and demoted by W. The channel gain involves two constituents, i.e., a large-scale path-loss and a small-scale Rayleigh fast-fading, where the Cost-Hata model [27] is used to calculate the large-scale path-loss. Furthermore, there are K arbitrarily positioned users, $p_k^{max} = 1$ watt, while the noise power spectral-density is 174 dBm/Hz.

A. INPUT DATA GENERATION

Primarily, the data is generated to train the DNN model utilizing our presented SAPARA Algorithm. To verify the precision of the solutions achieved from the SAPARA algorithm, we compare it with the EPESDR technique and optimal algorithms [3], [6], as shown in Figure 4. In the Optimal algorithm, the branch and bound (B&B) method is used to perform RRH-association and sub-channel assignment, and interior point algorithm (IPA) is used for power allocation. While in EPESDR algorithm, a distance-based RRH association is executed, the subchannels of a RRH are equally divided among its users, and power allocation is executed using an equal power distribution algorithm, which can be mathematically expressed as below

$$p_{k,n} = p_k^{max}/|N_k^m|, \quad \forall k, n \tag{15}$$

The simulation outcomes in Figure 4 show that our presented SAPARA algorithm outclasses the EPESDR, and is closed in performance to the Optimal algorithm in terms of EE against different parameters, e.g., different values of k, n and p_k^{max}. The SAPARA algorithm is better due to its lesser complexity and lesser run time. Therefore, we use our proposed SAPARA Algorithm for data generation. We generate about 22000 samples, of which 80% is used for training of our DNN model and the leftover for testing.

B. TRAINING THE DNN

Once the data is generated, the proposed model is trained with our labeled dataset. The labeled training dataset consists of input and output. To build and pre-train our presented DNN model, a stacked AE is used. Initially, an AE is trained with input data. To this end, following parameters are included in the first AE:L2 weight regularization = 0.004, transfer function = "sigmoid", sparsity regularization = 4, sparsity proportion = 0.15, epochs = 1000. The hidden codes of this AE are then produced by using the training data input as the AE input. These codes are then utilized for training the second AE. Using this method, several AEs are pre-trained, and finally, a SoftMax layer is added. For pre-training the SoftMax layer, the last AE hidden codes are used as the input while the output part of the labeled training dataset is used as a target.

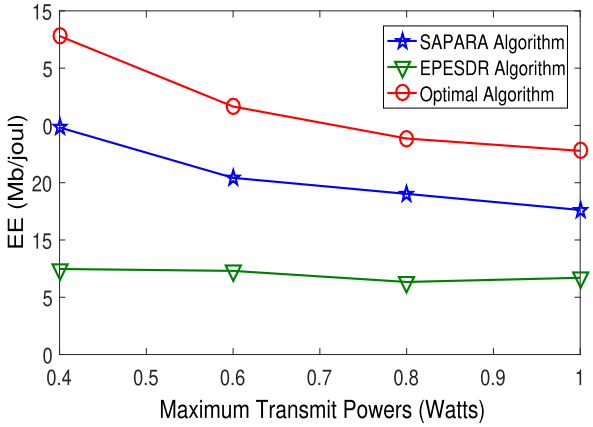

FIGURE 4. Performance comparison of our proposed joint SAPARA algorithm with optimal, and EPESDR algorithms.

C. RESULTS

1) EFFECT OF THE NUMBER OF HIDDEN LAYERS ON ACCURACY OF THE PREDICTION

Once the pre-training is done, all the AE encoders are stacked together with the Softmax layer, and the network is fine-tuned with our labeled training dataset. After completion of the training, model accuracy is tested through a labeled testing dataset. In order to discover the ideal count of hidden layers, the count of hidden layers is varied, and test accuracy is computed. Figure 5 illustrates the test accurateness of the presented model against the hidden layers count. It can be seen that initially, the accuracy rises as the hidden layers count increases, and then it begins to drop. A large number of hidden layers shows that more features can be learned. With a rise in the hidden layers, the model also begins to learn the data's noise. Therefore, the model cannot execute efficiently

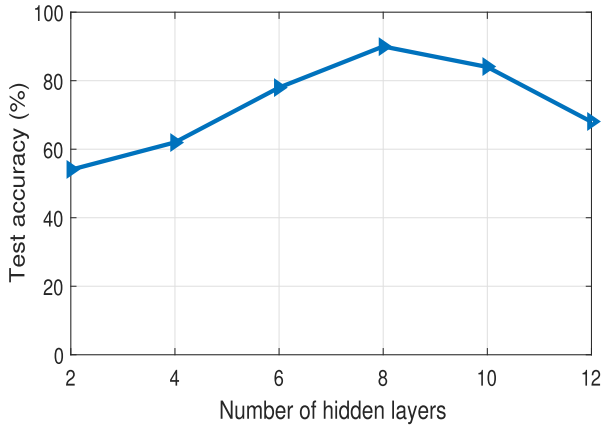

FIGURE 5. Prediction accuracy vs number of hidden layers.

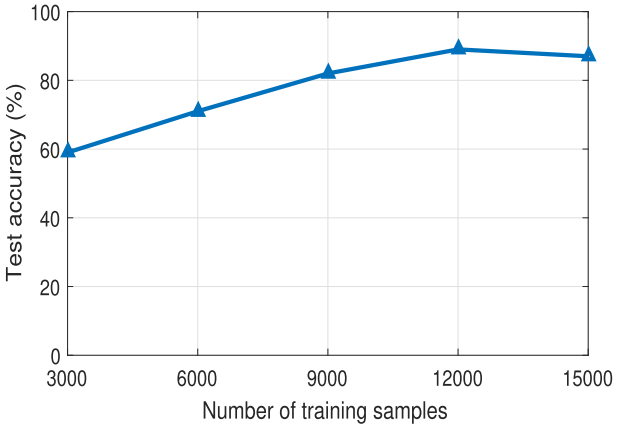

FIGURE 6. Test accuracy vs number of training samples.

on new samples, which deteriorates test accuracy. This brings overfitting to the training data for the said model.

2) EFFECT OF THE NUMBER OF TRAINING SAMPLES ON THE TEST ACCURACY

In Figure 6, it can be seen that the test accuracy is in direct proportion with the training samples count. Accuracy is low when the training samples count is small, and the accuracy rises steadily with a rise in the training samples. However, when the training examples count reaches some specified value, its saturation begins. The cause is that as we keep the size of the training sample rising, no new distinguishing features are there to be learned, and thus accuracy of the prediction test may not increase anymore.

3) EFFECT OF THE NUMBER OF TRAINING SAMPLES ON THE TRAINING ACCURACY

In Figure 7, it can be seen that the accuracy of the training is high for a small sample count, and it drops gradually with a rise in training examples count. When the number of training samples is small, the model learns a few distinguishing features, which is sufficient to show the input-output association of the training data. The accuracy of the training

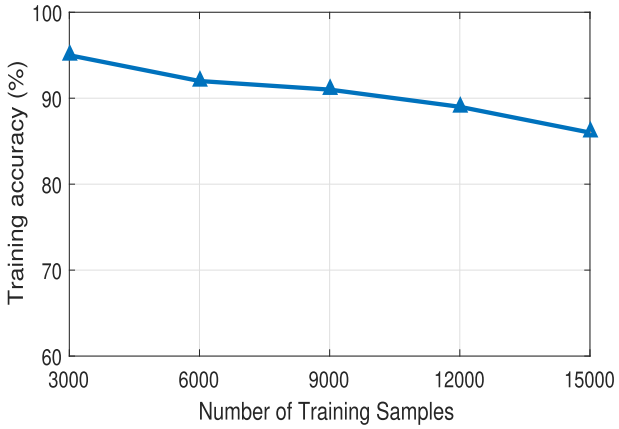

FIGURE 7. Training accuracy vs number of training samples.

is therefore high for a small training sample count. However, for testing purposes, the learned features are not satisfactorily adequate to correctly forecast the output. With a rise in training samples, more abstract features are extracted by the DNN model from the data. Consequently, the DNN model learns more related to the input-output association. However, the accuracy of the training drops because the model also starts learning the noise in data which eventually reduces the model performance. Ultimately, with a further rise in training data count, the DNN model begins to overfit the data, leading to decreased test accuracy.

VI. CONCLUSION

This paper proposed a supervised deep learning approach for a joint RA and RRH-association problem in multi-tier networks. Simulation results clarify that the prediction accuracy goes high with an increase in the number of data samples and hidden layers. But, a continuous rise in the hidden layers count will not increase the precision considerably, and in certain circumstances, the technique may initiate noisy learning features. Attaining the optimal arrangement of the DL technique, that is, the input data samples count and hidden layers count, is a challenging task. Moreover, it is vital to design fast offline techniques to produce optimum data samples to train the DNN model. Application of DL in scenarios with large network links and spatiotemporal correlations because of the mobility of users and changing channel features would be of instant significance.

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