

Received August 9, 2021, accepted August 17, 2021, date of publication August 24, 2021, date of current version September 1, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3107430

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

SHER ALI¹, AMIR HAIDER², MUHIBUR RAHMAN³, (Graduate Student Member, IEEE), MUHAMMAD SOHAIL^{1,4}, AND YOUSAF BIN ZIKRIA⁵, (Senior Member, IEEE)

¹School of Computer Science and Communication Engineering, Jiangsu University, Zhenjiang 212013, China

²School of Intelligent Mechatronics Engineering, Sejong University, Seoul 05006, Republic of Korea

³Department of Electrical Engineering, Polytechnique Montreal, Montreal, QC H3T 1J4, Canada

⁴Department of Computer Software Engineering, Military College of Signals, NUST, Islamabad 46000, Pakistan

⁵Department of Information and Communication Engineering, Yeungnam University, Gyeongsan-si 38541, South Korea

Corresponding authors: Muhammad Sohail (engrsohailaslam@gmail.com) and Yousaf Bin Zikria (yousafbinzikria@ynu.ac.kr)

This work was supported by Sejong University, Seoul, South Korea.

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 devices 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.

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Feng¹.

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

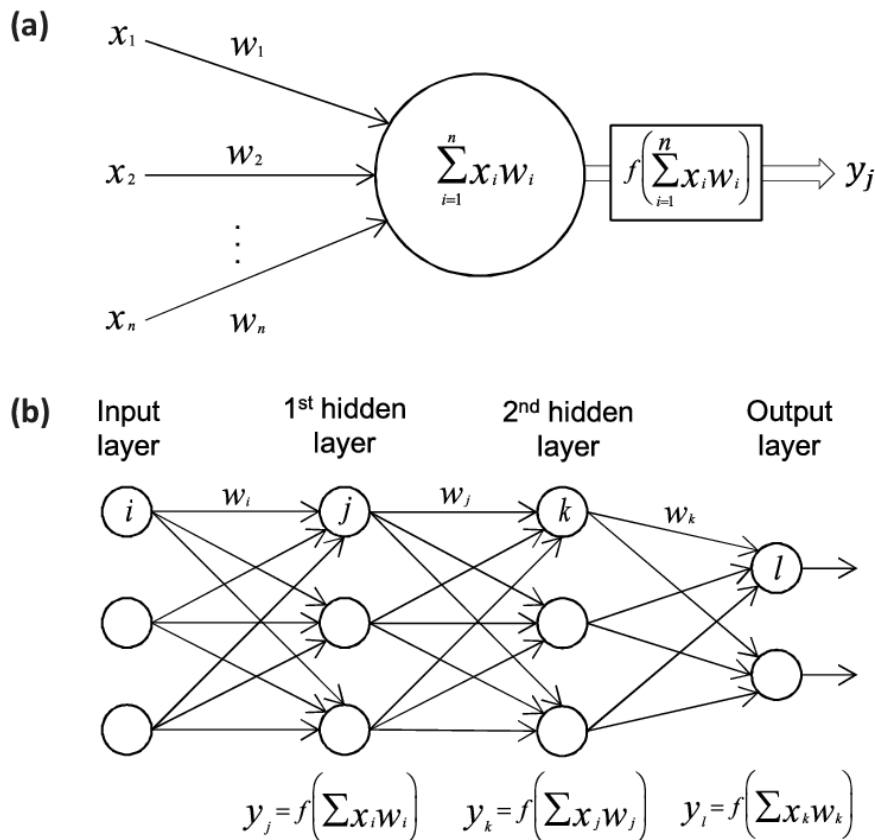


FIGURE 1. Illustration of a Deep Neural Network (DNN).

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)

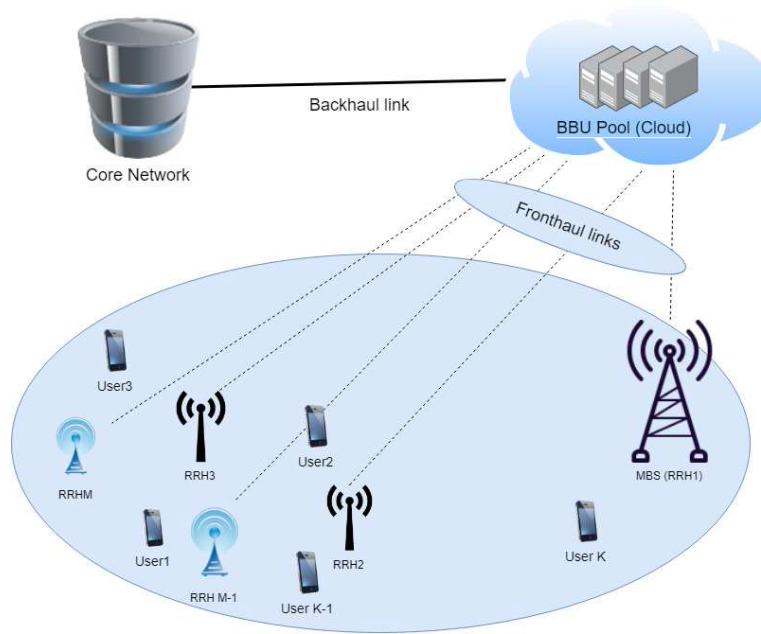


FIGURE 2. Illustration of multi-tier C-RAN.

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

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 k th user on n th 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 k th user on n th sub-channel to RRH m
$ h_{k,n}^m ^2$	Channel gain of k th user on n th sub-channel to RRH m
$I_{k,n}^m$	Interference on n th sub-channel of k th user to RRH m
$p_{l,n}$	Transmit power of the l th user on n th sub-channel
$ h_{l,n}^m ^2$	Channel gains of the l th user on n th sub-channel to RRH m
σ^2	Noise
$R_{k,n}^m$	Network sum-rate

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.

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

$$\sum_{n \in N_k^m} p_{k,n} \leq p_k^{max}, \quad \forall k, p_{k,n} \geq 0 \quad \forall k, n, \quad (2)$$

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:

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

where

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

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

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

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

$$\eta_k^m = \frac{R_k^m}{P_T^k} \quad (6)$$

where P_T^k shows the energy consumption of user k and comprises of two quantities: the collective transmit powers on all its subchannels $\sum_{n \in N_k^m} p_{k,n}$ 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:

$$P_T^k = \sum_{n \in N_k^m} p_{k,n} P_k^s + \varepsilon R_k^m \quad (7)$$

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

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

and the optimization problem is formulated as follows

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

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

$$C2: \sum_{m=1}^M \alpha_{k,m} = 1, \quad \forall k, \alpha_{k,m} \in \{0, 1\}, \quad \forall k, m \quad (11)$$

$$C3: N_k^m \cap N_j^m = \emptyset, \quad \forall k \neq j, \quad \forall m \quad (12)$$

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

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

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-linear 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 α^0 and p^0 , respectively, such that $\alpha^0 = \alpha_1^0, \alpha_2^0, \dots, \alpha_k^0$ and $p^0 = p_k^{max} / |N_k^m|, \forall k, n, m$. We perform initialization by UPA-PLA algorithm where

Algorithm 1 SAPARA Algorithm

```

1: Initialization  $K; N; M; \tilde{K} = \{1, \dots, K\};$ 
2:  $\tilde{N}^m = \{1, \dots, N\}; \tilde{M} = \{1, \dots, M\}; N_k^m = \phi, \forall k \in \tilde{K},$ 
3:  $\forall m \in \tilde{M}; N_k^{m,f} = \tilde{N}^m, \forall k \in \tilde{K}; R_k^{min}, \forall k; R_k^m = 0, \forall k, m$ 
4: while  $\tilde{M} \neq \phi$  do
5:   while  $\tilde{N}^m \neq \phi$  do
6:      $\forall k \in \tilde{K}_m^{m,f}$ 
7:      $\forall n \in N_k^{m,f} \cup \tilde{N}$ 
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:     $\tilde{N}^m \setminus n^*$ 
12:     $N_k^{m,f} = \{\min(N_{k^*}^m) - 1, \max(N_{k^*}^m) + 1\} \cap \tilde{N}^m$ 
13:     $R_{k^*}^m = W |N_k^m| \log_2 \left( 1 + \frac{1}{|N_{k^*}^m|} \sum_{n \in N_{k^*}^m} \left( \frac{p_{k^*,n} |h_{k^*,n}^m|^2}{\sigma^2 + I_{k^*,n}^m} \right) \right)$ 
14:    while  $(R_{k^*}^m < R_{k^*}^{min} \text{ and } N_{k^*}^{m,f} \neq \phi)$  do
15:       $\Delta \eta_{k^*}^m = f(\eta_{k^*}, N_{k^*}^m \cup n) - f(\eta_{k^*}, N_{k^*}^m), \forall n \in N_{k^*}^{m,f}$ 
16:       $n^* = \arg \max_{n \in N_{k^*}^{m,f}} \Delta \eta_{k^*}^m$ 
17:      Repeat steps 10 to 13
18:    end while
19:     $\tilde{K} \setminus k^*$ 
20:  end while
21:   $\tilde{M} \setminus m$ 
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 $N_k^{m,f}$ which shows the achievable subchannels set for k -th user connected to m -th RRH is set to have all the subchannels available initially therefore, $N_k^{m,f} = N$.

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 $\Delta \eta_{k^*}^m$ is found for each extra subchannel such that $n \in N_k^{m,f}$ (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 $\alpha = \alpha^i, p_{k,n}$ 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^{l+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 $\Delta \eta_{k^*}^m$ 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 $\Delta \eta_{k^*}^m$. 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.

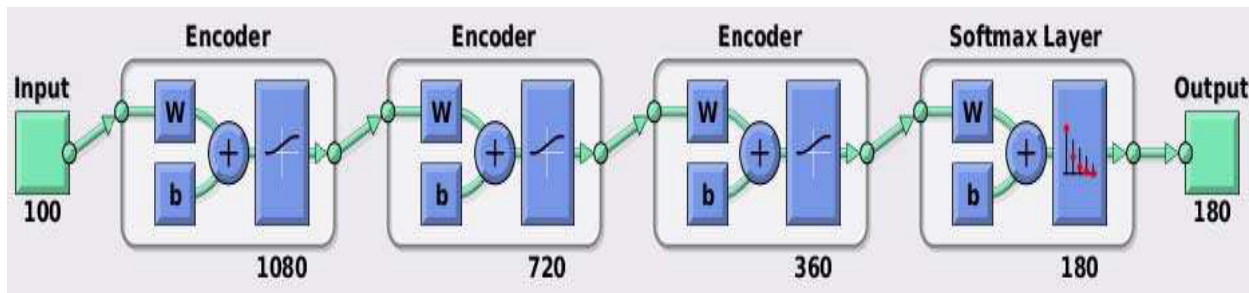


FIGURE 3. Our proposed DNN model.

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

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

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

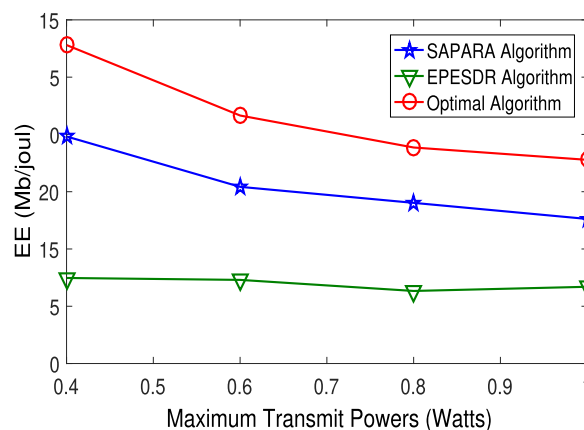


FIGURE 4. Performance comparison of our proposed joint SAPARA algorithm with optimal, and EPESDR algorithms.

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.

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

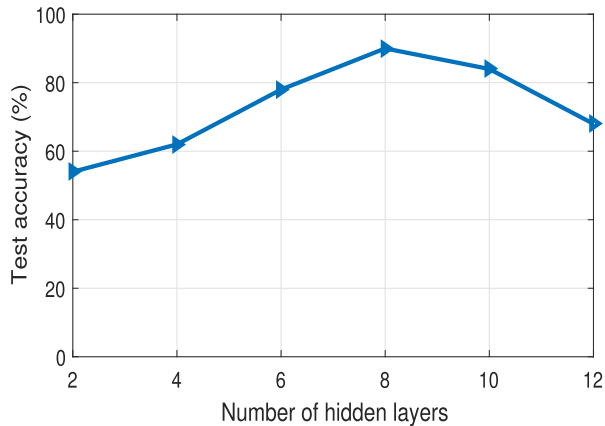


FIGURE 5. Prediction accuracy vs number of hidden layers.

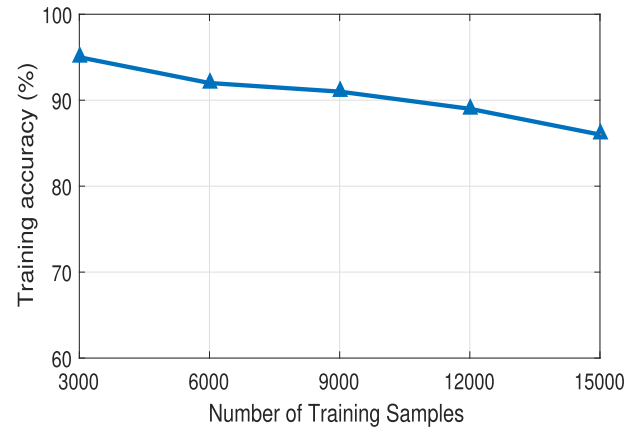


FIGURE 7. Training accuracy vs number of training samples.

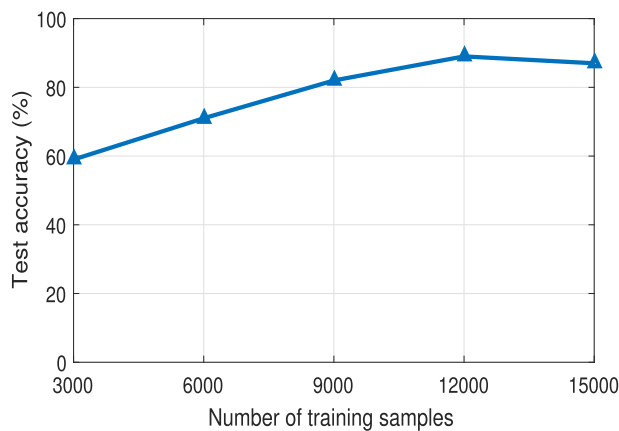


FIGURE 6. Test accuracy vs number of training samples.

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

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.

ACKNOWLEDGMENT

(*Sher Ali and Amir Haider are co-first authors.*)

REFERENCES

- [1] R. Ali, M. Sohail, A. O. Almagrabi, A. Musaddiq, and B.-S. Kim, "Green-MAC protocol: A Q-learning-based mechanism to enhance channel reliability for WLAN energy savings," *Electronics*, vol. 9, no. 10, p. 1720, Oct. 2020.
- [2] M. Sohail, R. Ali, M. Kashif, S. Ali, S. Mehta, Y. B. Zikria, and H. Yu, "TrustWalker: An efficient trust assessment in vehicular Internet of Things (VIoT) with security consideration," *Sensors*, vol. 20, no. 14, p. 3945, Jul. 2020.

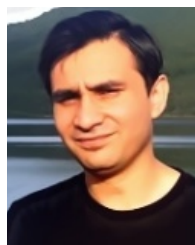
- [3] A. Sher, A. Ahmad, and A. Khan, "Energy-efficient resource allocation and RRH association in multitier 5G H-CRANs," *Trans. Emerg. Telecommun. Techn.*, vol. 30, no. 1, p. e3521, 2019.
- [4] C. Sun, C. She, C. Yang, T. Q. S. Quek, Y. Li, and B. Vucetic, "Optimizing resource allocation in the short blocklength regime for ultra-reliable and low-latency communications," *IEEE Trans. Wireless Commun.*, vol. 18, no. 1, pp. 402–415, Jan. 2019.
- [5] Y. Hu, M. Ozmen, M. C. Gursoy, and A. Schmeink, "Optimal power allocation for QoS-constrained downlink multi-user networks in the finite blocklength regime," *IEEE Trans. Wireless Commun.*, vol. 17, no. 9, pp. 5827–5840, Sep. 2018.
- [6] S. Ali, A. Ahmad, R. Iqbal, S. Saleem, and T. Umer, "Joint RRH-association, sub-channel assignment and power allocation in multi-tier 5G C-RANs," *IEEE Access*, vol. 6, pp. 34393–34402, 2018.
- [7] H. Sun, X. Chen, Q. Shi, M. Hong, X. Fu, and N. D. Sidiropoulos, "Learning to optimize: Training deep neural networks for interference management," *IEEE Trans. Signal Process.*, vol. 66, no. 20, pp. 5438–5453, Oct. 2018.
- [8] A. Zappone, M. Debbah, and Z. Altman, "Online energy-efficient power control in wireless networks by deepneural networks," in *Proc IEEE 19th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Kalamata, Greece, 2018, pp. 1–5.
- [9] F. Liang, C. Shen, W. Yu, and F. Wu, "Towards optimal power control via ensemble learning deep neural networks," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1760–1776, Mar. 2020.
- [10] L. Lei, Y. Yuan, T. X. Vu, S. Chatzinotas, and B. Ottersten, "Learning-based resource allocation: Efficient content delivery enabled by convolutional neural network," in *Proc IEEE 20th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Cannes, France, May 2019, pp. 1–5.
- [11] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Netw.*, vol. 2, no. 5, pp. 359–366, 1989.
- [12] P. Riley, "Three pitfalls to avoid in machine learning," *Nature*, vol. 572, no. 7767, pp. 27–29, Aug. 2019, doi: [10.1038/d41586-019-02307-y](https://doi.org/10.1038/d41586-019-02307-y).
- [13] Z. Xu, C. Yang, G. Y. Li, Y. Chen, S. Zhang, and S. Xu, "Energy-efficient configuration of spatial and frequency resources in MIMO-OFDMA systems," *IEEE Trans. Commun.*, vol. 61, no. 2, pp. 564–575, Feb. 2013.
- [14] C. Xiong, G. Y. Li, Y. Liu, Y. Chen, and S. Xu, "Energy-efficient design for downlink OFDMA with delay-sensitive traffic," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 3085–3095, Jun. 2013.
- [15] W. Yu, L. Musavian, and Q. Ni, "Statistical delay QoS driven energy efficiency and effective capacity tradeoff for uplink multi-user multi-carrier systems," *IEEE Trans. Commun.*, vol. 65, no. 8, pp. 3494–3508, Aug. 2017.
- [16] W. Yang, G. Durisi, T. Koch, and Y. Polyanskiy, "Quasi-static multiple-antenna fading channels at finite blocklength," *IEEE Trans. Inf. Theory*, vol. 60, no. 7, pp. 4232–4264, Jul. 2014.
- [17] Y. Zhu, Y. Hu, A. Schmeink, and J. Gross, "Energy minimization of mobile edge computing networks with finite retransmissions in the finite blocklength regime," in *Proc IEEE 20th Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Cannes, France, May 2019, pp. 1–5.
- [18] W. Lee, M. Kim, and D.-H. Cho, "Deep power control: Transmit power control scheme based on convolutional neural network," *IEEE Commun. Lett.*, vol. 22, no. 6, pp. 1276–1279, Jun. 2018.
- [19] A. Zappone, E. Björnson, L. Sanguinetti, and E. Jorswieck, "Globally optimal energy-efficient power control and receiver design in wireless networks," *IEEE Trans. Signal Process.*, vol. 65, no. 11, pp. 2844–2859, Jun. 2017.
- [20] H. Lee, S. H. Lee, and T. Q. S. Quek, "Deep learning for distributed optimization: Applications to wireless resource management," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2251–2266, Oct. 2019.
- [21] M. Chen, W. Saad, C. Yin, and M. Debbah, "Data correlation-aware resource management in wireless virtual reality (VR): An echo state transfer learning approach," *IEEE Trans. Commun.*, vol. 67, no. 6, pp. 4267–4280, Jun. 2019.
- [22] C. Zhang, H. Zhang, J. Qiao, D. Yuan, and M. Zhang, "Deep transfer learning for intelligent cellular traffic prediction based on cross-domain big data," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1389–1401, Jun. 2019.
- [23] I. Chaturvedi, Y.-S. Ong, and R. V. Arumugam, "Deep transfer learning for classification of time-delayed Gaussian networks," *Signal Process.*, vol. 110, pp. 250–262, May 2015.
- [24] *Study on Scenarios and Requirements for Next Generation Access Technologies*, document TSG RAN TR38.913 R14, 3GPP, 2017.
- [25] Y.-C. Wu, A. S. Debs, and R. E. Marsten, "A direct nonlinear predictor-corrector primal-dual interior point algorithm for optimal power flows," *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 876–883, May 1994.
- [26] J. Matousek and B. Gartner, "Integer programming and LP relaxation," in *Understanding and Using Linear Programming*. Berlin, Germany: Springer, 2007, pp. 29–40.
- [27] M. A. Nisirat, M. Ismail, L. Nissirat, and S. AlKhawaldeh, "Is Hata Path loss model a macro-cell model only? A question of debate," in *Proc. Int. Conf. Comput. Commun. Eng. (ICCCE)*, Kuala Lumpur, Malaysia, Jul. 2012, pp. 274–277.



SHER ALI received the B.S. degree from the University of Engineering and Technology at Peshawar, Peshawar, Pakistan, in 2009, the M.S. degree from CECOS University, Peshawar, in 2011, and the Ph.D. degree in electrical engineering from COMSATS University Islamabad, Pakistan. From 2012 to 2018, he served as a Faculty Member for the Department of Electrical Engineering, City University of Science and Information Technology, Peshawar. He is currently working as a Postdoctoral Fellow with Jiangsu University, China. His research interest includes resource allocation in wireless networks. He has also serving as an Associate Editor for many reputed journal, like IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS (Wiley) and IEEE ACCESS.



AMIR HAIDER received the B.S. degree in electronics engineering from International Islamic University, Islamabad, Pakistan, in 2012, the M.S. degree in electrical engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2014, and the Ph.D. degree from the Division of Electronics and Electrical Engineering, Dongguk University, Seoul, South Korea, in 2019. Before that, he has served as a Lecturer for the Department of Electrical and Computer Engineering, COMSATS University Islamabad, Pakistan, from August 2014 to August 2015, and later from September 2019 to February 2020 after completing of the Ph.D. degree. He was a Postdoctoral Researcher with the School of Intelligent Mechatronics Engineering, Sejong University, Seoul, from March 2020 to February 2021. He is currently working as an Assistant Professor with the School of Intelligent Mechatronics Engineering, Sejong University. His research interests include URLLC for beyond 5G mobile networks, artificial intelligence aided wireless communication systems, MIMO antenna design, optical communication systems, and wireless positioning technologies.



MUHIBUR RAHMAN (Graduate Student Member, IEEE) received the bachelor's degree in electrical (communication) engineering from the University of Engineering and Technology, Peshawar, Pakistan, in September 2014, and the M.S. degree in electrical engineering from NUST, Islamabad, Pakistan, in March 2016. He is currently pursuing the Ph.D. degree with Polytechnique Montreal, Canada. He worked as a Research Assistant with Lahore University of Management Sciences and Dongguk University, Seoul, South Korea. He has published number of index journals and conference proceedings and taken various patents. He is also an active peer reviewer and his name is placed in Top Peer Reviewer in Engineering by Publons.



MUHAMMAD SOHAIL received the bachelor's and master's degrees in telecommunications and computer networks engineering from the University of Engineering and Technology, Peshawar, Pakistan, in 2010 and 2016, respectively, and the Ph.D. degree in computer application technologies from the School of Computer Science and Telecommunication Engineering, Jiangsu University, China. From 2011 to 2013, he joined Oman Telecom Company Ltd., as a Network Operation Engineer. He is currently working with the Department of Computer Software Engineering, MCS, National University of Sciences and Technology, Islamabad, Pakistan. He is also associated with the School of Computer Science, Jiangsu University. His research interests include VANETs, information security, artificial intelligence, and software defined networks. He has served as a TCP Member for IEEE-ITIA held at Jiangsu, China, in November 2020. He is also serving as a Reviewer for *IET Information Security*, *Neural Computing and Applications*, *EURASIP Journal on Wireless Communications and Networking*, *Peer J Computer Science* journal, IEEE ACCESS, *Sustainable Cities and Society* and IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS.



YOUSAF BIN ZIKRIA (Senior Member, IEEE) is currently working as an Assistant Professor with the Department of Information and Communication Engineering, Yeungnam University, South Korea. He has held the prestigious CISA, JNCIS-SEC, JNCIS-ER, JNCIA-ER, JNCIA-EX, and advance routing switching and WAN technologies certifications. He has authored more than 90 articles, conferences, book chapters, and patents. He has published papers at the top venue, including IEEE COMMUNICATIONS, SURVEYS AND TUTORIALS, *IEEE Wireless Communications Magazine*, *Future Generation Computer Systems* (Elsevier), and *Sustainable Cities and Society* (Elsevier). He has managed numerous FT/SI in SCI/E indexed journals. His research interests include the IoT, 5G, machine learning, wireless communications and networks, WSNs, routing protocols, CRAHN, CRASN, transport protocols, VANETS, embedded systems, and network and information security.
<https://scholar.google.com/citations?user=K90qMyMAAAAJhl=en>
<https://sites.google.com/view/ybzikria>
<https://www.researchgate.net/profile/Yousaf-Zikria>

...