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Effective Resource Allocation Technique to Improve QoS in 5G Wireless Network

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Abstract: A 5G wireless network requires an efficient approach to effectively manage and segment the resource. A Centralized Radio Access Network (CRAN) is used to handle complex distributed networks. Specific to network infrastructure, multicast communication is considered in the performance of data storage and information-based network connectivity. This paper proposes a modified Resource Allocation (RA) scheme for effectively handling the RA problem using a learning-based Resource Segmentation (RS) technique. It uses a modified Random Forest Algorithm (RFA) with Signal Interference and Noise Ratio (SINR) and position coordinates to obtain the position coordinates of end-users. Further, it predicts Modulation and Coding Schemes (MCS) for establishing a connection between the end-user device and the Remote Radio Head (RRH). The proposed algorithm depends on the accuracy of positional coordinates for the correctness of the input parameters, such as SINR, based on the position and orientation of the antenna. The simulation analysis renders the efficiency of the proposed technique in terms of throughput and energy efficiency.

Keywords: centralized radio access network; base band unit; resource allocation; quality of service; channel state information; modulation and coding schemes

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1. Introduction

Technological advancements have increased the demand for high-speed and reliable network connections. This includes a better tele-networking facility (voice and video calls), online video streaming, and data download/upload [1]. 5G (based on a heterogeneous network) is used to cater to such demands in a mobile concept. It is a network- or user-centric service and is also referred to as a Centralized Radio Access Network (CRAN) [2]. The number of users is increasing exponentially day to day. Therefore, there is an inevitable requirement for efficient handling of this massive amount of network traffic while simultaneously maintaining high data-transfer rates. This increase in network traffic requires efficient implementation of a 5G network with high-speed data transfer and low latency [3]. 5G is intended to handle 1000× users in the current generation and decrease a minimum of 10× in latency levels [4]. The increased number of active users increases the difficulty in coordinating end-user (EU) devices and Remote Radio Heads (RRHs). CRAN is the perfect architecture to effectively implement in 5G [5].

It consists of RRHs that are made up of a widely distributed antenna system. These RRHs are placed separately from the Central Processing Unit (CPU). The CPU in this architecture is a cloud-based unit placed in an isolated environment known as the Base

Band Unit (BBU) [6,7]. A group of multiple BBUs is known as a BBU pool. Each RRH in CRAN architecture is connected to BBU by a dedicated optical fiber link. Within a particular geographical location, a densely distributed network of RRHs is known as an Ultra-Dense Network (UDN). The use of UDN results in low latency and improved performance [8].

The number of devices that participate in the network is always unpredictable. Therefore, a shorter frame duration is determined for Long-Term Evolution (LTE) compared to LTE advanced. Many end-user devices have allocated resources while maintaining system throughput and sum goodput. The traditional Resource Allocation (RA) technique uses Channel State Information (CSI). However, Mina et al. mentioned that RA involving CSI is more expensive in terms of system overhead and resource utilization [9]. The RA emphasizes information discovery and delivery as an internet-based architecture. It is referred to as an infrastructure network to make it more secure, as it addresses information and makes it routable. Several articles have been published to represent CRAN architecture with different resource allocation approaches, components, and other scenarios [4–8]. An illustration of the CRAN architecture is presented in Figure 1.

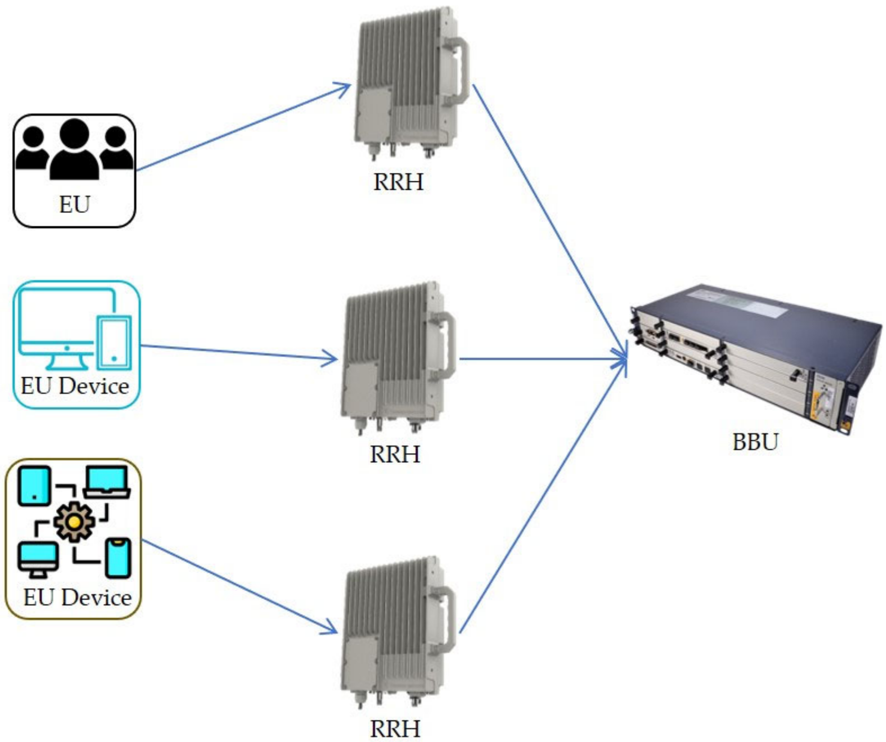

Figure 1. CRAN architecture.

In this work, we have discussed one of the most challenging RA using position information among BBUs in the BBU pool. The 5G network aims to provide high-speed data transfer with low latency. However, the overall increase in the number of active users put forth a challenge of an effective resource allocation process that is straightforward when using the traditional RA technique. The conventional RA technique uses CSI-based information, which requires an extensive overhead, making the process expensive [10].

The main objective is to propose a Resource Segmentation (RS) mechanism for 5G networks. To deal with this problem, we have developed a solution that considers the EU's position estimation for RA among BBU in CRAN. We have focused on minimizing operational expenses and power consumption. We proposed a modified RA scheme that efficiently handles the RA problem with a position-based RS technique that uses a modified Random Forest Algorithm (RFA), Signal Interference and Noise Ratio (SINR), and EU position coordinates. The improved RA helps enhance the quality of service (QoS) in 5G wireless networks. This RS technique takes various parameters (such as energy efficiency and throughput) as input, then predicts the Modulation and Coding Schemes (MCS). It establishes a connection between the EU device and the RRH. It mainly focuses on the CAPital EXpenditure (CAPEX) and OPerational EXpenditure (OPEX) of the 5G network. In the simulation analysis, the proposed position-based modified RA scheme is improved throughput, i.e., 2.5 Mbps, through user variation compared to the CSI-based RA scheme and learning-based scheme. Then, the proposed CRAN has improved energy efficiency of 2.65 (bps/Hz/W) compared to the existing H-CRAN (Heterogeneous-based Cloud Radio Access Networks), as it takes the value of 2.5 (bps/Hz/W).

This paper is organized as follows. Section 2 presents the developments related to improvements in the 5G wireless networks. The CRAN-based system architecture and its RA methodology with modified position coordinates are discussed in Section 3. The modified RA scheme is discussed in Section 4. Finally, the simulation analysis of the proposed scheme is presented in Section 5.

2. Related Works

The 4GLTE and Long-Term Evolution Advanced (LTE/A) use packet switching based on Internet Protocol (IP). LTE's primary concern is handling fluctuating users within a geographical area. Network fluctuation is achieved through the channel prediction based on the acquisition of resources among the users utilizing Machine Learning (ML)-based Multiple Input Multiple Output (MIMO). It helps to improve CSI accuracy with data compression and processing delay [11], as well as imperfect CSI with channel rate adaption [12]. However, this technique is inefficient when applied to 5G networks because of the enormous traffic load. In their research [13], the authors have proposed the allocation of resources based on an approximation algorithm connecting end-users with respective RRH. The approximation algorithm found the approximate number of end-users connected with a particular RRH. Then, it established a connection between the end-user and RRH and between RRH and BBU. In [14], the authors have clearly described the resource allocation scheme with the combination of a new radio and LTE network, which overcomes the problem of computational complexity and overhead signal in a centralized approach. Based on the proposed HCCRRA, power consumption and throughput were improved based on the users' packet arrival rate variation. Thus, the allocation strategy can be applied based on varying time scales and congestion control policies in the next generation of 5G networks [15].

Huan et al. in [16] considered the challenge of millimeter-wave (mmWave) beamforming and an optimized time-delay pool based on hybrid beamforming (for single and multiple user scenarios in 5G CRAN networks). An energy-efficient scheme was designed based on resource provisioning [17] by considering the network traffic based on resource demand in the CRAN network. Using a resource provisioning scheme, they considered the problem of optimizing and managing the resource. The authors formulated the resource allocation based on the Graph Convolutional Networks (GCNs) [18]. They have proved that the proposed method gains significant improvement concerning communication complexity in wireless networks [19]. As it is a denser network, more resources are utilized, increasing the energy efficiency of the process. In [20], the cooperative model is proposed to integrate transmission and power consumption, which uses proposed resource allocation based on the water filling model to improve the energy efficiency with the difference in the end-user.

Similarly, in [21], the authors suggested a resource allocation mechanism that uses Random Forest Algorithm and a system scheduler to validate the output from the binary classifier. Although the algorithm performs well in terms of robustness, research and further development are limited. The authors of [22] proposed using the Random Forest Algorithm to create a classifier using a supervised machine-learning strategy. The authors considered using the ID3 decision tree to classify the input parameters used. Moreover, the SINR was kept constant while allocating resources. However, the value of SINR is subject to dynamic changes; thus, we may be unable to obtain the optimum resource allocation.

After investigating various approaches such as RRH tier, High Power Node (HPN) tier, and HCRAN for resource allocation among BBU in CRAN, the traditional method of RA uses CSI-based information of the End User (EU) in fifth-generation (5G) network. Due to an enormous increase in system overhead—approximately 25% of the overall system capacity—the conventional RA scheme is not optimal for application in CRAN for a 5G network [23].

The traditional CSI-based RA scheme also fails to provide optimum results when the system's total number of users increases. Moreover, the decision tree used in the prediction of MCS in machine-learning-based RA schemes is ID3, which is inefficient when learning or test data consist of missing values. ID3 decision trees also fail to address the solution for overfitting. During machine learning, the data pre-processing and data classification improve the accuracy of the prediction process [24]. The resource computation based on a scheduling framework paves the way for managing the resource based on data reliability [25]. Effective resource segmentation is proposed in [26], which discusses CRAN's benefits in managing resource-allocation effectiveness. Then, the proposed strategy paved the way for applying the existing random forest algorithm concerning RRH with MCS schemes. The analysis has been carried out for average throughput over the number of users and scatters density. Various RA-based approaches are summarized in Table 1.

The author suggests using the End User (EU) position estimates to deal with these challenges. The EU's position estimates can be supplied as input in our proposed machine-learning-based supervised learning RA scheme, generating a C4.5 decision tree to allocate MCS to the EU [27]. Therefore, the authors take this opportunity to propose an efficient RA scheme for implementation in the CRAN system for the 5G network. Thus, our proposed strategy states the objective of effective resource allocation through a modified random forest algorithm to integrate a decision tree [28,29].

Table 1. Existing works based on resource allocation.

S.N.	Paper Title	Proposed Methodology	Research Gap and Future Work
1	Energy-efficient 5G cloud RAN with virtual BBU server consolidation and base station sleeping [13]	A H-CRAN model based on resource-aware power consumption performs a dynamic centralized RRH switch OFF mechanism based on small cells as it helps to minimize the probability of outage and energy consumption.	Offloading tasks can be performed to save energy in cloud computing based on the mobile environment
2	RBF-SVM-Based Resource Allocation Scheme for 5G CRAN Networks [14]	A learning-based Radial Basis Function (RBF) support vector machine (SVM) is proposed for allocating the resource, as it estimates the user's position based on the resource block and size of the packets.	Various classifier algorithms can be applied to analyze throughput and classification parameters.
3	Optical true time delay pool-based hybrid beam former enabling centralized beamforming control in millimetre-wave C-RAN systems [16]	An optical true time delay pool-based hybrid beamforming (OTTDP-HBF) scheme is enabled with centralized beamforming with computational processing in the control unit.	Different pre-coding schemes for single-user and multi-user scenarios are analyzed based on spectral efficiency.
4	Deep-Reinforcement-Learning-Based Resource Allocation for Content Distribution in Fog Radio Access Networks [30]	A deep reinforcement learning (DRL)-based resource allocation scheme is proposed to improve the distribution of content and address the problem of resource allocation in the radio access network	Offloading schemes based on the cooperative network can be performed on routing decisions based on a network resource.
5	Training Resource Allocation for User-centric Base Station Cooperation Networks [31]	A graph-theoretic approach based on a user-centric cooperative network to minimize the overhead of data training for large-scale network	Resource allocation problem. The proposed approach can be applied to orthogonality via time/frequency.

3. System Architecture

The key idea of the proposed architecture is to deploy CRAN based on resource segmentation for 5G networks, which considers the problem of end-users pure-position estimates as the basis for resource allocation among BBU. Here, the CRAN architecture and its essential components are discussed initially. Then, the resource allocation process is based on BBU with proper connection establishment between the EU and RRH to estimate the SNIR and transmission power. The position is calculated based on RRH user entry in CRAN on a per-frame basis.

3.1. General Trivia and Assumptions

CRAN is a unified architecture for use in a 5G network. Some of the essential components for the same are represented in Figure 2.

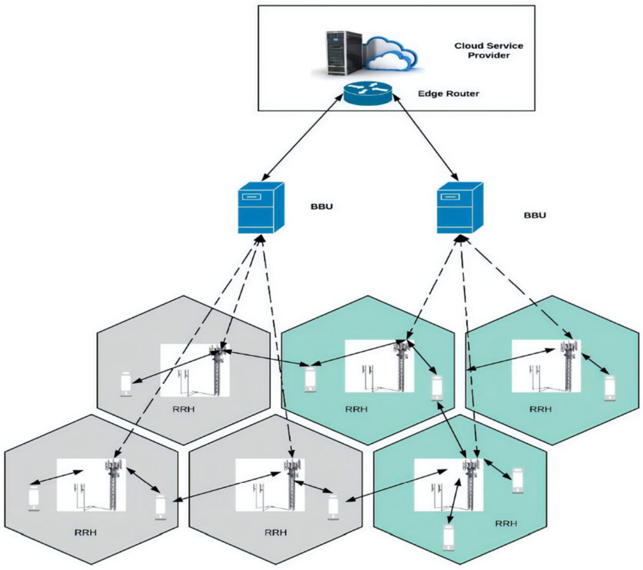

Figure 2. Modified C-RAN Architecture.

1. Base Band Unit (BBU) consists of an isolated cloud-based CPU. The CPU is responsible for baseband processing. Each BBU is capable of handling one or more RRRHs at the same time.
2. RRH is an isolated unit of the remotely distributed antenna system. The combination of multiple RRHs is referred to as UDN. Each RRH is connected to a BBU with the help of a dedicated optical fiber link.
3. N represents the EU device. Each EU is connected with an RRH through a wireless communication channel.
4. RRH and EU devices contain transmission and receiving antennas, with A_Tx represented as the transmission antenna and A_Rx described as the receiving antenna. CRAN allows the antenna system to be installed over any high-rise structure such as a building, streetlight, etc.
5. CRAN functions in Time Division Duplex (TDD) and Orthogonal Frequency Division Multiplexing (OFDM).
6. It is assumed that only one EU is connected to the RRH at a given time.

3.2. Resource Allocation in CRAN

The CRAN system consists of BBU as the cloud-based central processing unit. This unit provides the entire baseband processing required whenever the system detects a new EU, as mentioned in Figure 3. During the resource allocation process, first, the EU is assigned to an RRH on a per-frame basis. Following the assignment of EUs assigned to the RRHs, an assignment matrix is generated for the same, represented as ω^t.

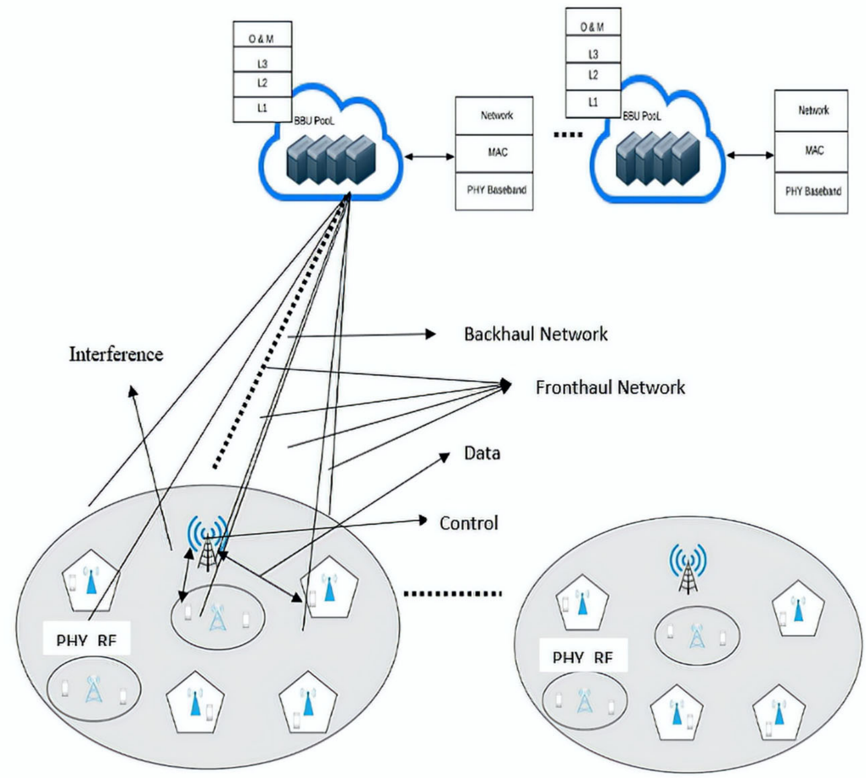

Figure 3. Resource Segmentation among BBU and RRH.

For an established connection between EU and RRH at a given time t, transmission depends on the interference of the transmission medium. For a combination of given RRH and EU at time t, SINR is given by using Equation (2) in (1),

$$SNIR_q^t = \frac{TP_{p,q}^t}{\sigma^2 + \sum_{\substack{s=1, \\ s \neq p}}^{R} TP_{s,q}^t} \tag{1}$$

where $TP_{p,q}^t$ represents the total power of the signal received by EU q, from the p^{th} RRH, at time frame t, $TP_{s,q}^t$ depicts the total power of the signal received by EU q, from the sth RRH, at the time frame t, and σ^2 defines the total power of noise. Therefore, the total signal power received $TP_{p,q}^t$ is given by

$$TP_{p,q}^t = TP_{tp} \cdot \left| T_{p,q}^t \cdot Cm_{p,q}^t \cdot R_{p,q}^t \right|^2 \tag{2}$$

TP_{tp} indicates the amount of transmit power provided per RRH, and $Cm_{p,q}^t$ represents the channel matrix (CM) for time frame t between RRH_x and EU_n. Each component of the channel matrix shows a channel impulse. The channel impulse [32] is the aggregate of all the impulses generated from multiple parts between A_{Tx} and A_{Rx} and is given as

$$K_{{}^{a}_{x}R,{}^{a}_{x}T}(t,\alpha) = \sum_{m=1}^{M} \bar{k}_{m,{}^{a}_{x}R,{}^{a}_{x}T}(t) \cdot e^{\frac{l2\pi b_m(t)}{\lambda}} \cdot \delta\left(\alpha - \alpha_{m,{}^{a}_{x}R,{}^{a}_{x}T}(t)\right) \tag{3}$$

M represents the number of multiple path components; $\bar{k}_{m,{}^{a}_{x}R,{}^{a}_{x}T}(t)$ represents the impulse response from m^{th} multipath, also consisting of the path loss. Wavelength is represented by λ, and b_m is used for total distance by multiple path m at time frame t. $\delta\left(\alpha - \alpha_{m,{}^{a}_{x}R,{}^{a}_{x}T}(t)\right)$ is used for the delta function, which represents the evolution of response from channel impulse following different multiple path delays $\alpha_{m,{}^{a}_{x}R,{}^{a}_{x}T}(t)$.

3.3. Estimation of Position Coordinates

When a new user enters the CRAN system, it is assigned to an RRH. This assignment is based on position estimates. A module which is a known system overhead module is required to obtain either of the two parameters. Consider the time frame representation, as in [33], where the total frame duration t_f is 1ms and consists of S = 2 sub-frames, each with the duration t_{sub}. The initial units of each sub-frame were used to estimate location coordinates and the unit of time frame represented by narrowband beacons was the basis for position estimation. Wideband beacons were used to estimate position estimates based on information in traditional resource-allocation techniques. The total number of units needed to evaluate the position depended upon the total number of EU in the system. Unused units in a particular time frame can be used for data traversal in the transmission channel [34].

Based on the above-discussed parameters, the percentage overhead required to estimate position on a per-frame basis was calculated using

$$SO_{pos} = \frac{SY_{pos} \cdot f_{subc,pos}}{SY_{total} \cdot f_{subc.total}} \tag{4}$$

where, SY_{pos} represents the number of OFDM symbols used for position estimation of EU in the CRAN system, $f_{subc,pos}$ represents the total number of sub-carriers used to find the position, and SY_{total} and $f_{subc.total}$ represent the total number of OFDM symbols and sub-carriers available in the time frame t_f. Following the calculation of SO_{pos}, it was taken as the input value for adding a new RRH to handle the traffic demand of one MBS network.

4. Proposed Scheme

In this section, we discuss our proposed scheme, a supervised learning-based RA scheme that uses position estimates of the EU to predict the Modulation and Coding Scheme (MCS). Based on the C4.5 decision tree [35], the efficient link between EU and RRH for high-speed data transfer has been proposed for meeting the challenges mentioned in the problem statement, as represented in Figure 4. The proposed scheme for RA is based on the Random Forest Algorithm (RFA). This algorithm helped with the creation of a forest of random binary decision trees with each solution for some given input parameters. RFA is dependent on the training dataset to generate binary decision trees. The training dataset T_d was made up of two parts: an input feature vector and output values, with the RFA taking inputs from the input feature vector. Thus, it developed C4.5 binary trees γ_t with depth γ_d, which are capable of handling missing data and overfitting problems.

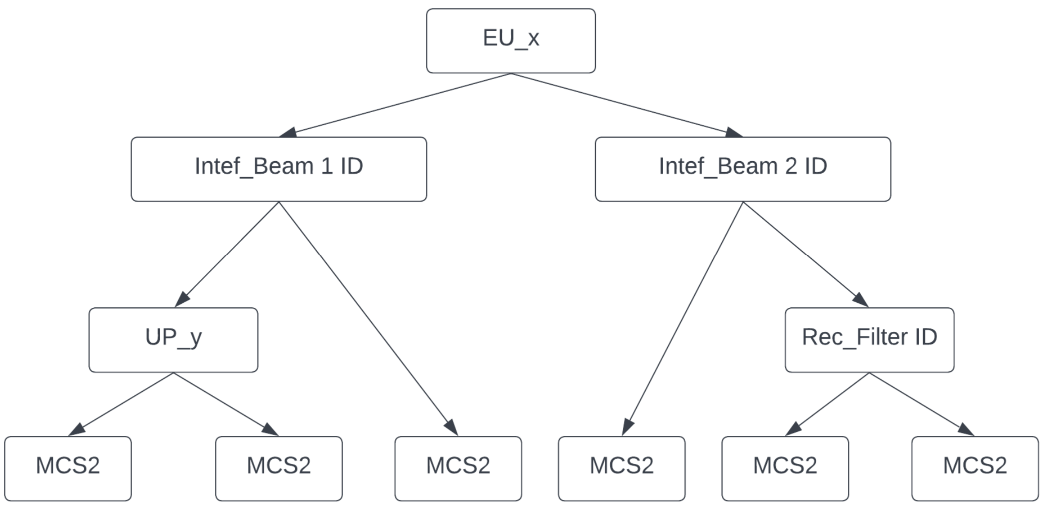

Figure 4. Position estimation of EU based on MCS.

The input feature vector consists of the following elements:

- $R_x \rightarrow$ Receive filter value for a particular EU to RRH assignment at time t.
- $T_x \rightarrow$ Transmit filter value for a particular EU to RRH assignment at time t.
- SINR $\rightarrow$ The value of interference and noise ratio.
- $PE_n^t \rightarrow$ As shown in Figure 4, the value of position estimates obtained from the time frame beacons.
- $ITB_y \rightarrow$ The value of interfering transmit beam for assignment of n^{th} EU to q^{th} RRH.

The proposed machine-learning-based model was trained with the help of real-time data instances obtained from various telecom service providers. The data consisting of actual EU to RRH assignment details and their transmit beam, receive filter, and MCS values were fed into the system for practical training. Following the training of the system, test data were used to test the model's credibility. After rigorous training and testing, the model was finally used to predict MCS for a given EU to RRH assignment. Figure 3 depicts an example of a C4.5 random binary decision tree which is a part of a generated Random forest, and the C4.5 decision tree generation is represented in Algorithm 1.

Algorithm 1. Modified C4.5

Input: Dataset Ds;
Output: Decision Tree DT, Error Rate of Node N;

```
Begin
Construct Tree Node T with Root Node RT
Then, Root RT → classifies the dataset
If (Node T → Attributes {1, 2, . . . n})
RT1 → RT + Branch B;
Return RT1;
Elseif (Node T — Empty)
BranchB = N;
Assign N as Class D;
Return N;
Elseif (Node T — Same category D)
Leaf node = N;
Mark N as class C;
Return N;
Else
Add a new branch added to the node T;
For (i = 1 to n)
{
Calculating the Attribute Information Gain;
}
Ta → Attribute Testing;
Highest Information Gain → Ta * N;
//Tree Splitting for each Tree T
If (T is Empty)
Leaf Node → Child Node N;
Else
Decision Tree DT → Child Node N;
Calculate the Error Rate of Node N;//Missing Rate
Return N;
End
```

C4.5 decision trees have been used to predict MCS from input parameters. A C4.5 tree was seen as better than the conventional Iterative Dichotomiser 3 (ID3) tree due to its ability to handle missing data values. It also works well to overfit values. The binary tree has a depth $\gamma_d = 3$, as shown in Figure 3. Further, a tree could be traversed for the optimal solution. Leaf nodes in the binary decision tree represent various MCSs to enable the establishment of the EU and RRH. A rigorous search technique was used to determine input parameters for constructing training data. As soon as the training is complete, the testing phase begins. The random forest algorithm is one of the most efficient algorithms used to generate multiclass classifiers, as represented in Algorithm 2. Following the obtainment of predicted MCS value from the random binary tree, it calculated the sum goodput using,

$$g_{x,n}^{t} = \frac{\left(1 - e_{mcs_{x,n}^{t}(\tau_n^t)}\right) \cdot d_{mcs_{x,n}^{t}}}{T_f} \tag{5}$$

In Equation (5), $g_{x,n}^{t}$ represents the sum goodput, $e_{mcs_{x,n}^{t}(\tau_n^t)}$ represents the total block error rate, and $d_{mcs_{x,n}^{t}}$ represents the payload for a specific value of MCS.

Equation (5) considers the factors required to calculate the sum of the goodput, specifically to establish the connection between EU and RRH and the predicted value of MCS. Table 2 provides details of the percentage contribution and the data type of input parameter attributes in the input feature vector.

Table 2. Contribution value and data type of input attributes.

Variable Name	Data Type	Range	Variable Value
SIR	Integer	1–7	8.7
End User_x	Float	270.5–283.5	10.3
End User_y	Float	65–205	14.9
Transmit Beam	Integer	1–28	14.3
Receive Filter	Integer	1–7	15.5
Interference Beam 1	Integer	1–28	13.4
Interference Beam 2	Integer	1–28	10.8
Interference Beam 3	Integer	1–28	12.1

Algorithm 2. Modified Random Forest

Input: Decision Tree DT Data sets;
Output: Random binary tree

1. **Begin**
2. **Select** T → ST;//To grow the number of trees
3. **Initialize** S → Bagging data;
4. **For** S = 1 to T
5. Training Data TD → construct the sample Sa in S of size N;
6. Developing Random Forest Ra to S
7. Repeat steps 4 to 6;
8. Terminate till the node minimum value is attained.
9. Assign variable at random Vr from S variables in
10. Node T;
11. Select the best split tree from Vr;
12. Divide node N into two leaf nodes;
13. Random binary tree
14. **End**

Interference beams 1, 2, and 3 interfere with various EU transmit beams. EU_x and EU_y are the position coordinates of the EU as calculated from the narrowband beacons of the time frame. The receive filter and transmit beam represent these elements' percentage necessity in the input feature vector.

5. Simulation Analysis

This section briefly describes the methodology used to support the author's proposed scheme for effectively segmenting resources among BBU in centralized radio access networks. All the simulations for this model were conducted on ns2. The simulation uses 100 RRH with a transmission power of 25 dBm and a packet size of 1000 bits for the CRAN network. The transmission range assigned in the network of 500m, and used to analyze the channel state information, OFDMA_QPSK_1_2, is used as the modulation type. During the traffic demand, 6.4 Mbps~200 Mbps data were used with the network bandwidth of 20 MHz.

The proposed scheme also intends to evaluate the performance of the random forest algorithm as in Algorithm 2. In this performance analysis, resource allocation parameters, i.e., energy efficiency and QoS guarantee, were evaluated based on the proposed system. Based on the simulation configuration, we evaluated the performance of the proposed system as represented in Table 3.

Table 3. Simulation Configuration.

Parameters	Value
Transmission Range	500 m
Packet Size	1000 bits
Modulation Type	OFDMA_QPSK_1_2
User distribution	Uniform
Total bandwidth	20 MHz
Traffic Demand	6.4 Mbps~200 Mbps
Number of RRH	100
RRH maximum Transmission power	25 dBm
Antenna gain for RRH	6 dB

5.1. Analysis of Channel Estimation

Before deploying the random forest, it is necessary to check the integrity of the dataset for training purposes. The trained model's test dataset was given as input to check its accuracy. Training accuracy was judged based on validation by test data. Research has already been conducted to evaluate the effectiveness of the Random Forest Algorithm. An OFDM system based on pilot channel estimation adds the pilot into the OFDM symbols of the subcarrier in the uniform interval of time. The channel estimation over the Least Square (LS) is estimated to calculate Minimum Mean-Square Error(MMSE) with a signal-to-noise ratio (SNR).

$$\hat{h}_{LS,i}\ (n) = \hat{h}_i(n) + \hat{w}_i(n),\ 0 \leq n < N \tag{6}$$

where

$\hat{h}_{LS,i}\ (n) \rightarrow$ Time-domain Noise over $\hat{w}_i(n)$

$\hat{h}_i(n) \rightarrow$ Time-domain estimated channel impulse response

There is a limitation of channel correlation elimination while deploying the linear MMSE. This technique helps to estimate the pilot frequencies at the channel and intercalate them. The OFDM channel estimation provides the data symbols at the periodic time interval using pilot-based channel estimation, as all the data sub-carriers are used as pilots. The advantage of this channel estimation is that there is no error. The channel estimation is performed based on fast and slow fading.

Channel estimation techniques help to enhance the performance of the Orthogonal Frequency Division Multiplexing (OFDM) system in terms of Symbol Error Rate (SER), and thus, the channel estimation accuracy improves. Compared to the traditional technique, the performance of the proposed model can be seen in the graph shown in Figure 5. The proposed algorithm has helped to increase the average network throughput compared to the currently used learning-based and CSI-based systems for the same number of active EUs. The network throughput showed consistently high overall value ranges for the same number of users compared to the CSI-based system. At first, the graph does not show a vast difference between the two series. However, many system performances were seen with an increase in the number of users in the system. The graph shows the appreciable difference between the three series until users increase to a specific value. Following this, both series decrease on the average network throughput value. The algorithm proposed by the authors can be considered an improvement over the convolutional strategy.

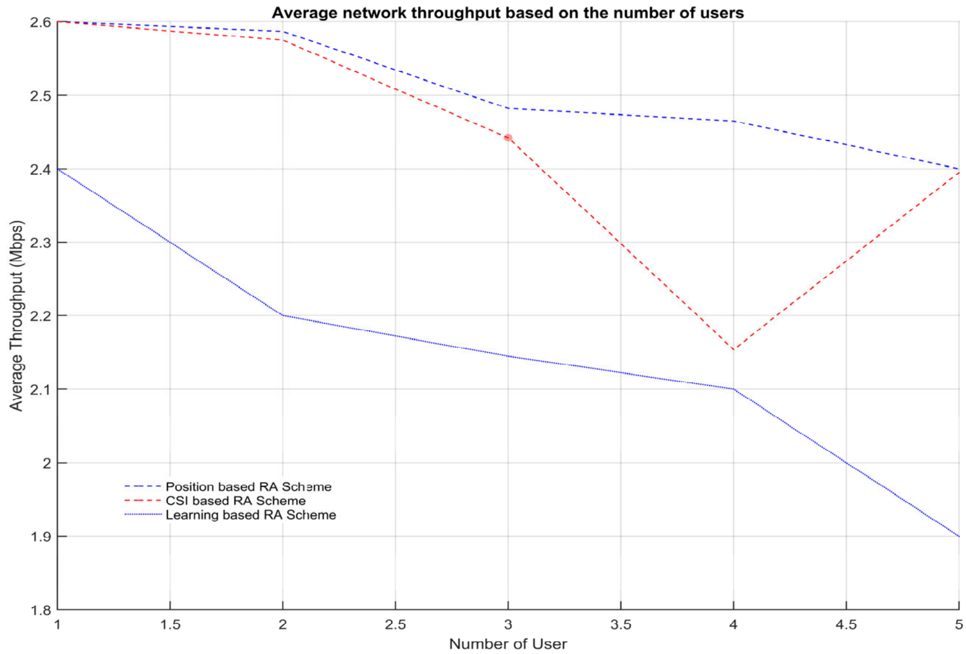

Figure 5. Average network throughput based on the number of users.

The average network throughput was analyzed by considering the position coordinates based on the modified RA scheme discussed in Section 4 and represented in Figure 5. The coordinate position information generated was based on all RRH with the comparison of existing learning-based and CSI-based RA schemes.

Figure 6 shows the inference of the network throughput values and the overhead generated for each RA scheme. Analysis shows the CSI-based RA scheme having an average of 2.45 Mbps throughput compared to the learning-based RA scheme. However, the proposed position-based modified RA scheme has 2.5 Mbps throughput, improving the value compared to the CSI-based RA scheme. With the high network density, a profound change was seen in the scatter density based on the obstacles, analogous to the graph shown in Figure 6. This depicts the average network throughput for the increasing number of users, showing the average network throughput for various values of scatter density along the *x*-axis. This graph also shows the authors' proposed scheme outperforming the conventional technique, which uses CSI. The average network throughput in both graphs does not show any predictable trend. However, the performance of the position-based scheme was seen as better than that of the traditional CSI-based RA scheme.

Figure 7 shows the analysis of the average network throughput based on the variation in the number of samples. Generally, the CSI-based RA scheme has better network throughput and improved variation compared to the learning-based RA scheme. The authors proposed a position-based modified RA scheme that averages 2.46 Mbps network throughput compared to the CSI-based Ra scheme with 2.44 Mbps. For the simulation, we used 3,00,000 samples for the performance evaluation, and the result shows that the proposed scheme has better throughput than the learning-based and CSI-based RA schemes.

5.2. Analysis of Energy Efficiency

Section 5.2 analyzes the performance of UE coordination to guarantee the Quality of Service (QoS) based on energy efficiency. The RA scheme has been proposed, and an analysis of the connection between the UEs and RRHs was conducted based on MCS using the proposed RS technique. This RS technique integrates the random forest along with the C4.5 algorithm multiple binary decision trees.

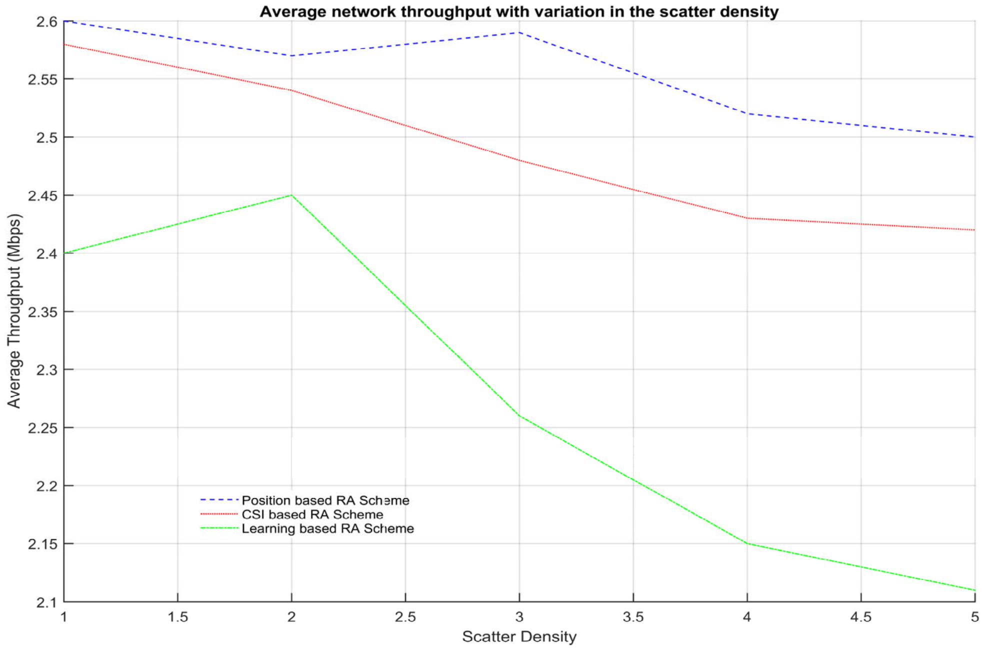

Figure 6. Average network throughput with variation in the scatter density.

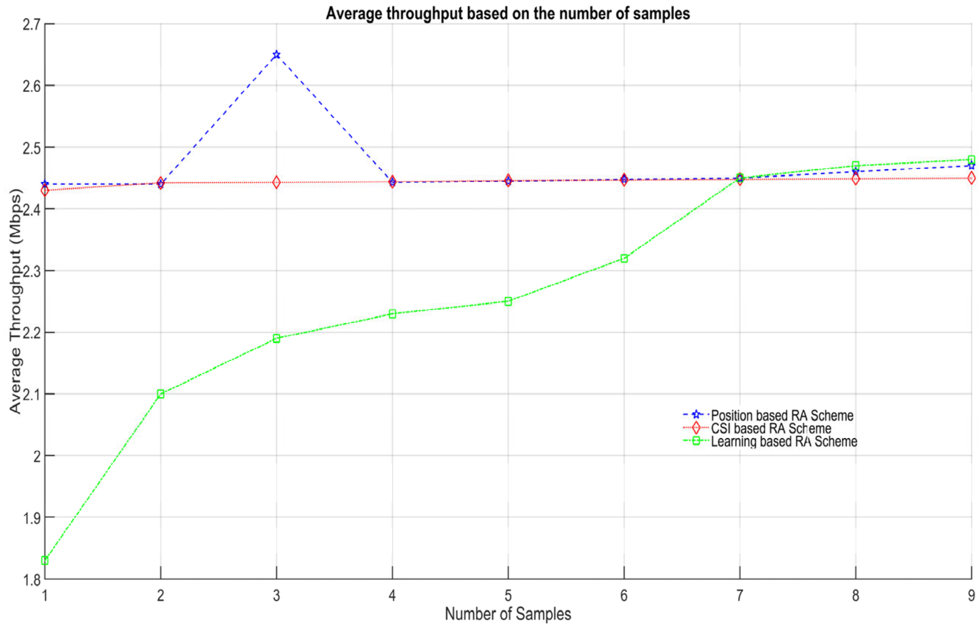

Figure 7. Average throughput based on the number of samples (in thousands).

Figure 8 presents an analysis showing the proposed enhanced C-RAN compared with the other two methods. The proposed improved C-RAN scheme achieves up to 2.38 bps/Hz/W, which provides better energy efficiency than the RRH Tier, C-H-CRAN. The authors have analyzed the UE system coordination by calculating the energy efficiency based on the SNIR threshold value, with variations from 0 to 16, as shown in Figure 9. The proposed Enhanced C-RAN has an energy efficiency of 2.65 (bps/Hz/W) compared to H-CRAN, which takes the value of 2.5 (bps/Hz/W). Despite the increase in the limit of the SNIR value, the proposed enhanced C-RAN value decreases to 2.58 (bps/Hz/W). It provides higher energy efficiency than existing techniques such as RRH Tier C-RAN, H-CRAN, and office-based RRH tier, i.e., RRH tier-based structure is established for the office community.

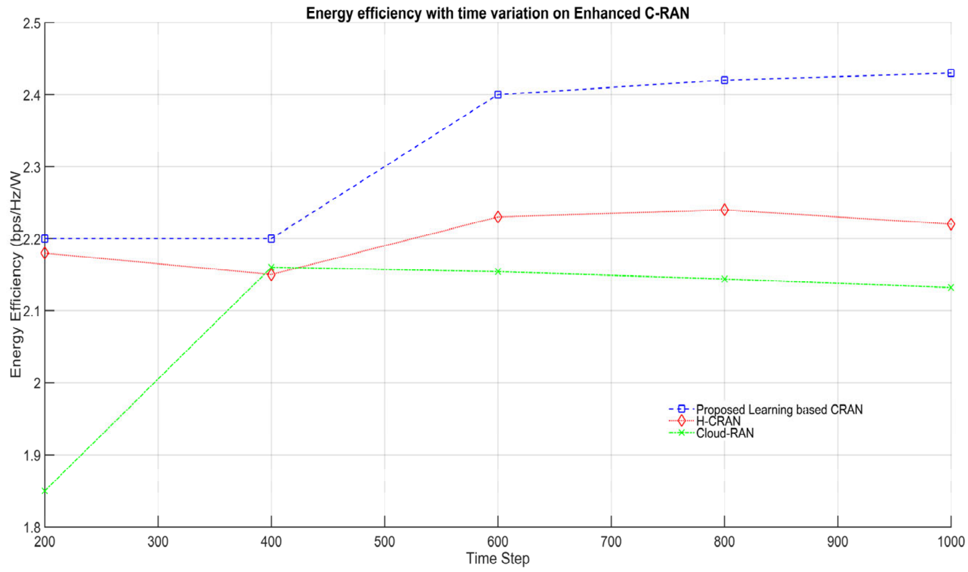

Figure 8. Energy efficiency with time variation on Enhanced C-RAN.

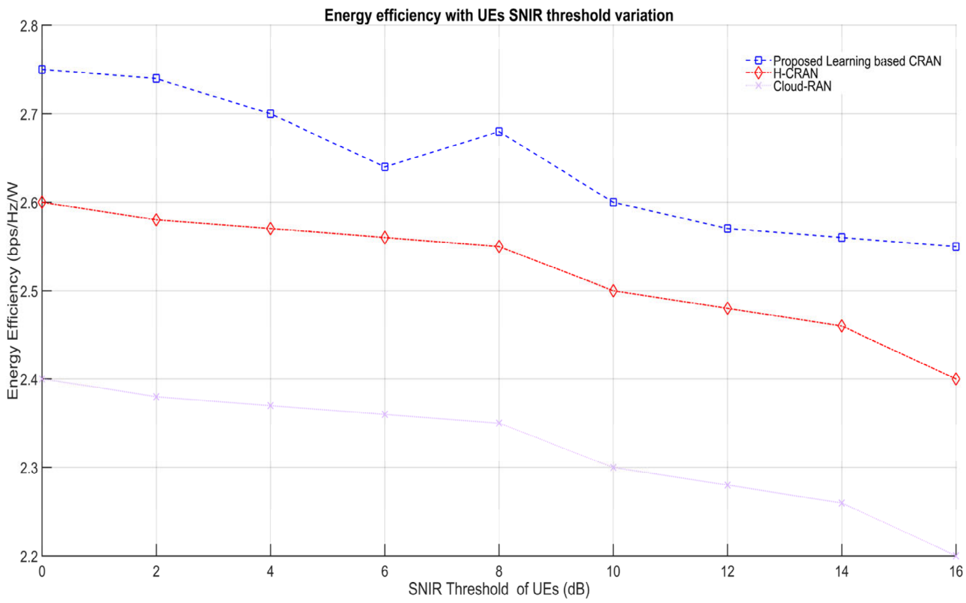

Figure 9. Energy efficiency with UE's SNIR threshold variation.

5.3. Analysis of throughput with Iteration Variation

Figure 10 shows the calculation of average throughput based on the variation in the iteration from 2 to 10. The authors have fixed the uniform transmission power for all the RRH to evaluate the network throughput and the maximum transmission power to 0.5 W. based on the variation in the number of iterations. The proposed enhanced C-RAN has the constant value of 2.38 (nats/symbol) compared to other existing techniques such as RRH Tier, C-RAN, H-CRAN, and improved network throughput.

5.4. Analysis of Resource Allocation Based on the Distribution Function

The Cumulative Distribution Function (CDF) value is determined based on the evaluation of the data rate accessed by user equipment based on resource block = 1000, and efficiency is analyzed based on the threshold of 2 Mbps, 0.5 Mbps and 4 Mbps. The proposed learning-based CRAN outperforms the existing approaches, such as H-CRAN and Cloud-RAN, as in Table 4.

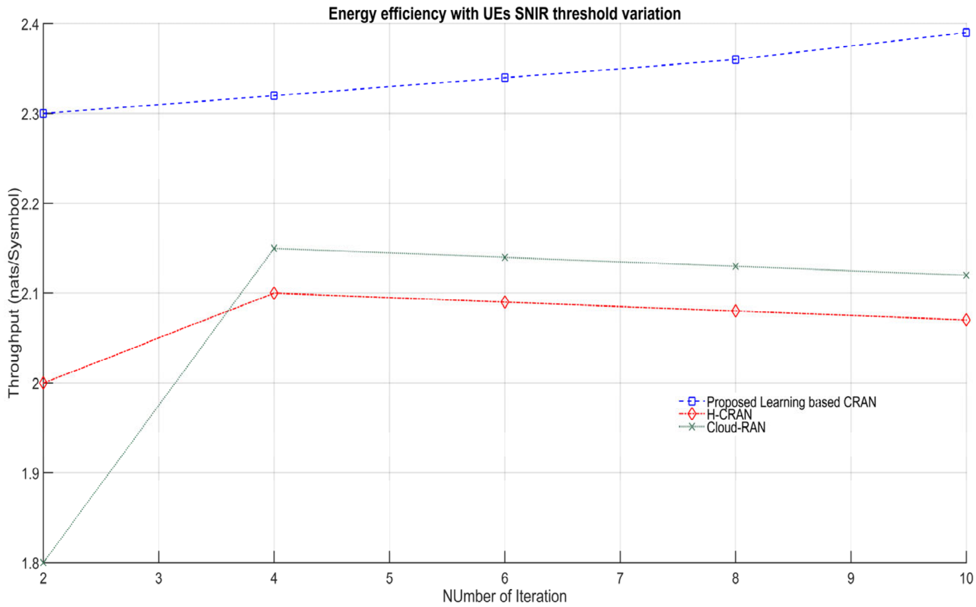

Figure 10. Throughput analyses based on the variation in iteration.

Table 4. CDF-based data rate by accessing resource allocation.

S. No.	Cumulative Distribution Function (CDF)		
Methods	**Cloud-RAN**	**H-CRAN**	**Proposed Learning-Based CRAN**
0	0.0	0.0	0.0
1	0.432	0.132	0.125
2	0.865	0.400	0.312
3	0.985	0.765	0.745
4	1.000	0.950	0.912

6. Conclusions

Recent advancements in the IT sector have created an unprecedented demand for reliable network connections. High-speed data transfer has become the primary need of almost every internet user. However, considering a massive number of IoT for deploying an efficient resource allocation is a required strategy. The conventional resource allocation strategy uses a CSI-based scheme for resource allocation in LTE and LTEA. However, the vast increase in the volume of EU's has brought about the need for employment of next-generation 5G networks. Resource allocation in 5G using conventional methodology is not efficient enough.

For the same reason, we have proposed a resource allocation scheme based on supervised machine learning, and RA helps enhance the security in 5G Wireless Networks. This strategy uses the Random Forest Algorithm to generate a multiclass prediction system or classifier. The scheme proposed by the authors uses pure position-based estimates of the EU's to predict the MCS. The random Forest Algorithm creates a forest of C4.5 random binary trees. Leaf nodes of these trees represent the value of MCS for use in a particular EU to RRH assignment. Suppose that in the tree, there is a possibility that more than one value of MCS is predicted for the EU-RRH connection for the same input parameters. In that case, the model of all the MCS values is considered. The model evaluation section shows that the proposed scheme's performance works better than the traditional resource allocation technique using CSI-based information. As throughput and energy efficiency parameters are considered, the proposed model performs better, and those parameters are QoS metrics, reflecting the improvement in the QoS.

Figures 5 and 6 clearly show that the author's proposed algorithm performs better for a dynamic EU load. However, after the number of users increases to a specific value, the performance of both algorithms starts to deteriorate. Therefore, the proposed strategy may not be the best for resource allocation. However, it portrays another approach to resource allocation among BBUs in centralized radio access networks. In the future, advanced learning methods can be associated with CRAN in 5G networks as it takes improved network overall performance.

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