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Wireless 5G Network in Edge Computing Based On MIMO with Federated Learning and Clustering Integrated Reinforcement Learning

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Abstract

Edge Computing (EC) is a revolutionary architecture that brings Cloud Computing (CC) services closer to data sources than ever before. This research proposed novel technique in edge computing network based on wireless 5G technology using MIMO_federated learning integrated with Reinforcement neural network. Here the aim is to enhance the resource allocation by Decentralized Federated learning in multiple user based MIMO (De_Fed_L- MIMO) networks. Then the energy efficiency and channel optimization of the network is carried out using K-means clustering integrated with Reinforcement learning (K-means_RL). Here the experimental analysis is carried out in terms of number of users of network as well as number of edge server by DoF of 92%, Spectral efficiency of 92%, Energy efficiency of 96%, Signal to noise ratio (SNR) of 85%, Coverage area of 92%, RL training accuracy of 95%, FL training accuracy of 98%.

Keywords: Edge Computing, MIMO, 5G cellular networks, federated learning, resource allocation, energy efficiency and channel optimization

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1. Introduction

Wireless communication networks are transitioning from smartphone-centric to an IoT-oriented method that connects billions of small as well as power-limited devices [1]. As a result, optimization of a large number of network parameters will be required in next-generation communication systems. Any resource allocation choice is converted into an optimization issue if an accurate mathematical model that characterises performance metric exists [2]. Solving such an optimization issue appears to be a simple process [3]. As a result, the difficulty of fixing these issues grows exponentially as number of radio parameters grows, which for future networks will be significantly greater than for existing wireless networks. Furthermore, any time one of the system parameters changes its value, which happens

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relatively frequently in high mobility situations due to shorter channel coherence time, resource allocation decision must be repeated. Federated machine learning is a new decentralised approach that takes into account the issues highlighted above, such as privacy and resource limits. As an extension of original federated technique proposed by Google recently [4].Both training time as well as global model accuracy are critical criteria in Federated Learning (FL). As a result, lowering time it takes for communications to arrive becomes a critical concern. The available radio resources in network vary over time due to highly dynamic wireless channel conditions and the transmission of local method parameters from various IoT devices to edge server at various periods [5]. In meanwhile, because future traffic loads are unpredictable, radio resource allocations for distinct traffic tasks are linked. Because global method is created based on local model parameters in federated learning, as opposed to centralised ML on the remote cloud, this may reduce model accuracy. As a result, global model correctness remains a significant issue in federated learning, particularly when edge server processing and storage resources are restricted .

Research paper is as follows: 1.To propose novel technique in edge computing network based on wireless 5G technology using MIMO_federated learning integrated with Reinforcement neural network. 2.To enhance the resource allocation by Decentralized Federated learning with MIMO. 3.To improve energy efficiency and channel optimization of the network using K-means clustering integrated with Reinforcement learning .

2. Related Work

A number of reviews on uses of DL in 5G wireless mobile networks can be found in the literature. As a result, this section of the report was dedicated to presenting reviews as well as highlighting discrepancies with current review. For instance, work [7] conducted a survey on use of DL methods in anomaly detection. It primarily focused on 5G wireless mobile network's cyber security defensive mechanism. Another study found that [8] were motivated by the fact that millimetre wave (mmWave) and ultra wideband communications are heavily used in 5G wireless mobile networks. As a result, it concentrates on the wireless mobile networks' physical layer. Similarly, in [9], a survey concentrating on DL method based physical layer, specifically NOMA, massive MIMO and mmWave, was provided. In [10], the author presented a temporal CNN for mmWave outdoor positioning in 5G mobile wireless networks. DL was presented by author [11] for the distribution of cooperative resources in 5G mobile wireless networks. In [12], the author advocated using CNN to capture characteristics of interfering signals to suppress them. Suggested CNN-MU-MIMO for 5G is used to reduce interference, which is linked to lower computational complexity as well as increase performance of CNN- MU-MIMO. CNN was proposed in study [13] for development of a system to identify distributed DOF attacks triggered by a botnet that controls malicious devices via a 5G network. The authors of [14] examine FL as well as its applications in 5G networks, as well as future directions. Authors [15] provide a complete overview of FL as well as a detailed tutorial on the problems and applications of FL-MEC. Work [16] provides a thorough examination of the role of FL in attaining the objectives of 6G communication systems. The authors of this study explore the fundamental obstacles in deploying FL in wireless networks as well as present some key ideas to address these issues. [17] present a summary of advancements, evaluation metrics, problems, literature classification, and future directions of FL in context of IoT networks. Furthermore, in [18], the authors give a complete assessment on FL for wireless communications improvements, with a focus on grouping current research utilizing a multi-level classification method. [19] present a comprehensive examination of intersection of FL and edge computing, focusing on problems, applications, security and tools. Authors [20] provide a comprehensive summary of FL's latest achievements as well as applications in automotive networks and IoT. Work [21] presents a complete assessment on deployment of distributed learning methods over wireless networks, with a particular emphasis on communication efficiency of all DL methods. Furthermore, study [22] provides a thorough examination of the requirement for effective signal processing. Future wireless network scenario in which FL is utilized to train a global method in a distributed manner. However, because FL must transmit method via both uplink as well as downlink channels, federated training will only be useful if wireless network's efficiency is excellent.

3. System Model

This section proposed novel technique in edge computing based resource allocation with network energy enhancement and channel optimization. The correctness of the framework's model is investigated in this section under constraints of wireless channels, restricted storage and processing capacity of edge servers. Because learners include IoT devices like sensors, drones, autonomous vehicles. In the meantime, given edge servers' limited storage and computational capacity, total number of IoT devices. Proposed figure is shown in

Figure 1. In this instance, communications delay becomes a critical component in deciding aggregated model's performance. These devices may have distinct channel circumstances while approaching a BS, necessitating a varied amount of spectrum resources to complete their traffic responsibilities. We must concentrate on two aspects when given a traffic task foreach end device: 1) how to better allocate spectrum resources to reduce task communication latency; 2) how to ensure that different jobs' QoS requirements in terms of maximum communications delay

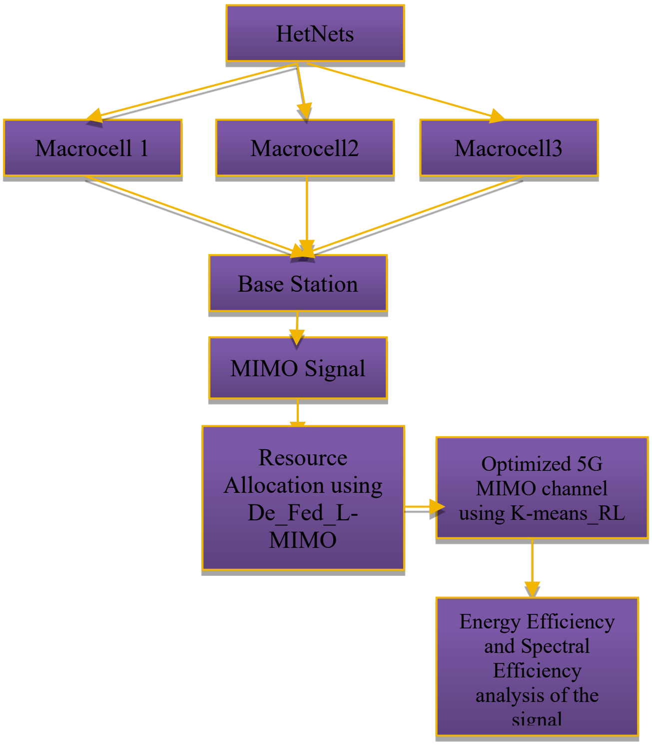

Figure 1. Prosed Architecture diagram

are met. Because latency is such an important parameter for FL, it's best to keep communications latency as low as feasible for as many traffic activities as possible. Here, ηi is spectral efficiency (bits/sec/Hz) based on corresponding end device channel state, xi is number of resource blocks allotted to job I and li is length of task i.

Channel model:

$$\mathbf{H}^{[k,i]} = \sqrt{\beta^{k,i]}}\mathbf{G}^{[k,i]} \qquad (1)$$

Where $\mathbf{H}^{k,i]} \in \mathbb{C}^{N_r \times N_t}, i = \{1,2,\cdots,M\}$ and $k = \{1,2,\cdots,K\}$. Scalar $\beta^{k,i]}$ signifies matrix of small-scale fading coefficients, while $\mathbf{G}^{k,i]} \in \mathbb{C}^{N_r \times N_t}$ reflects large-scale propagation losses.Distance-dependent path loss is defined as $\beta^{|k,i]} = \zeta^{[k,i]}\chi^{[k,\vec{\imath}]}$ with $\chi^{[k,i]}\zeta^{[k,i]}[\mathrm{dB}] = -\left(\zeta_0 + 10\alpha\log_{10}\left(r^{[k,i]}\right)\right)$is 3D path loss.

Resource allocation by Decentralized Federated learning in multiple user based MIMO:

Set of devices is denoted by N = {1, ..., N}, and set of communication links is denoted by G = (N, E), which is an undirected graph with vertex set N and edge set E. Collection of device i's linked neighbours is indicated by$\mathcal{N}_i = \{j \mid (i,j) \in \mathcal{E}\}$ Taking up problem of distributed stochastic optimization in eq. (2),

$$\underset{\theta \in \mathbb{R}^d}{\operatorname{minimize}} F(\boldsymbol{\theta}) \triangleq \frac{1}{N}\sum_{i=1}^{N} f_i(\boldsymbol{\theta}) \qquad (2)$$

$f_i(\boldsymbol{\theta}) = \frac{1}{|\mathcal{D}_i|}\sum_{\xi \in \mathcal{D}_i} f_{i,\xi}(\boldsymbol{\theta})$ is local loss function at device i and F(θ) is global loss function.

The two sections of the designed communication model are as follows:

1) Scheduling: In this research, we look at D2D communication as a way to increase communication performance. Graph colouring method is used to determine an appropriate scheduling scheme for reducing the number of transmission blocks.
2) Transmission: Received signal at enrolled receiving device I is expressed as at the transmission block t in eq. (3).

$$\boldsymbol{y}_i^t = \sum_{j \in \mathcal{N}_i} h_{ij}^t \boldsymbol{x}_j^t + \boldsymbol{z}_i^t \qquad (3)$$

The transmit signal $\boldsymbol{x}_j^t$ encapsulates data of local model $\boldsymbol{\theta}_j^t$, and the additive noise vector $h_{ij}^t \in \mathbb{C}$ represents channel coefficient between devices $\boldsymbol{\theta}_j^t$ and $z_i^t \in \mathbb{C}^d$ at transmission block t.

Loss Function

With loss function $f(\mathbf{w}, \mathbf{x}_i, y_i)$ the main aim is to determine method parameter $\mathbf{w} \in \mathbb{R}^d$that characterises output yi. For the data sample$\mathbf{x}_i$, we rewrite $f(\mathbf{w}, \mathbf{x}_i, y_i)$ as $f_i(\mathbf{w})$.

$$F_k(\mathbf{w}) \triangleq \frac{1}{D_k}\sum_{i \in \mathcal{D}_k} f_i(\mathbf{w}) \qquad (4)$$

$$\min_{\mathbf{w} \in \mathbb{R}^d} F(\mathbf{w}) = \sum_{k \in \mathcal{K}_{\text{tot}}} p_k F_k(\mathbf{w}) \qquad (5)$$

where $p_k \triangleq \frac{D_k}{D \text{ is weighting factor for of UE } k}$, satisfying $p_k \geq 0$ and $\sum_{k \in \mathcal{K}_{\text{tot}}} p_k$

$$f_i'(\mathbf{w}) \triangleq f_i(\mathbf{w}) + \frac{\mu p_k}{2}\|\mathbf{w} - \mathbf{w}_s\|^2 \quad \forall i \in \mathcal{D}_k \qquad (6)$$

2-regularized linear regression method$f_i'(\mathbf{w}) = (1/2)\|y_i - \mathbf{w}^T\mathbf{x}_i\|^2 + (\mu/2) \parallel \mathbf{w} \parallel^2$.Following are our observations.

3) In some extreme instances, UE μk may have a vast amount of data, and the user's local model is largely

dictated by the most recent global model. The coefficient µk in (6) safely reflects varying amounts of local data at UE k, whereas a set proximal term for all UEs is less adaptable. As a result, the local updates at UE k in (7), (8) are changed as follows:

$$\mathbf{w}_{g,\ell+1}^{k} := \mathbf{w}_{g,\ell}^{k} - \lambda_{g,\ell} \nabla F_{k}'\left(\mathbf{w}_{g,\ell}^{k}, \xi_{g,\ell}^{k}\right) \quad (7)$$

$$:= \mathbf{w}_{g,\ell}^{k} - \lambda_{g,\ell}\left(\nabla F_{k}\left(\mathbf{w}_{g,\ell}^{k}, \xi_{g,\ell}^{k}\right) + \mu p_{k}\left(\mathbf{w}_{g,\ell}^{k} - \mathbf{w}_{g}\right)\right) \quad (8)$$

Algorithm 1 summarises proposed FL design. A small but significant change in step 10 of Algorithm 1 is likely to result in efficient performance gains.

Algorithm of De_Fed_L- MIMO:

Input: $K_{tot}, K_g, L, G,$ *and* $\mathcal{D}_k, \forall k, g$
Start global method w_0 *and learning rate* λ_0 *to same value for all UEs*
for $g = 0,1,\cdots,G-1$ *do*
for $k \in \mathcal{K}_g$ *in parallel do*
$\boldsymbol{w}_{g,0}^{k} = \boldsymbol{w}_g$
for $\ell = 0,1,\cdots,L-1$ *do*
Randomly pick a data point $\xi_{g,\ell}^{k} \in \mathcal{D}_k$
Update: $\boldsymbol{w}_{g,\ell+1}^{k} := \boldsymbol{w}_{g,\ell}^{k} - \lambda_{g,\ell}\left(\nabla F_k\left(\boldsymbol{w}_{g,\ell}^{k}, \xi_{g,\ell}^{k}\right) + \mu p_k\left(\boldsymbol{w}_{g,\ell}^{k} - \boldsymbol{w}_g\right)\right)$
end for
Send $w_{g+1}^{k} := w_{g,L}^{k}$ *to BS end for*
end for
$\boldsymbol{w}_{g+1} := \frac{1}{K_g}\sum_{k\in\mathcal{K}_g} \boldsymbol{w}_{g+1}^{k}$
End for

Energy efficiency and channel optimization using K-means clustering integrated with Reinforcement learning (K-means_RL):

Clustering is a well-known unsupervised ML method. The clustering algorithm's goal is to segregate each category's sample points and produce a centroid for each. As a result, for each category, we utilise clustering technique to group channel vectors with similar channel characteristics and design codewords. One of the most often utilized methods, K-means, has been optimised. Unlike the K-means algorithm, which obtains the first centroids by chance, the K-means algorithm has a more complicated initialization. The initial centroids are determined first, and then the centroids are updated using the K-means algorithm.

A distance metric based on angles between users is presented for K means clustering method. Method divides users into K clusters, with each user belonging to cluster with closest centre. Clusters' centres are initially random, but once users have been clustered, they are re-evaluated. Users are clustered as well as centres are re-evaluated in numerous iterations. When centres of clusters do not differ by more than a user-defined percentage, algorithm converges.

Determination of initial centroids Mf = {me 1, me 2, me 3, ..., me K]} needs3 steps:

Step 1: We pick first initial centroid, me 1, at random from X.

Step 2: For every xi(i = 1, 2,...,P) in X , from existing initial centroids, calculate cumulative distance between them eq. (9):

$$D(\mathbf{x}_i) = \sum_{j=1}^{t} d\left(\mathbf{x}_i, \tilde{\mathbf{m}}_j\right) \quad (9)$$

The chance of x i being chosen as next initial centroid is then calculated as follows eq. (10):

$$P(\mathbf{x}_i) = \frac{D(\mathbf{x}_i)}{\sum_{i=1}^{P} D(\mathbf{x}_i)} \quad (10)$$

Step 3: Steps 1 and 2 should be repeated until we get K initial centroids. The initial centroids are obtained using the three processes above, and the gap between them is kept as little as feasible. It can overcome the problem of K-means being substantially influenced by the random selection of initial centroids. The nearest neighbour rule states that xi will be linked with the q-th centroid if distance between mq(q = 1, 2,...,K) and xi is the shortest in eq. (11).

$$q = \underset{q=1,2,\ldots,K}{\arg\ \mathrm{m}}\ d\left(\mathbf{x}_i, \mathbf{m}_q\right) \quad (11)$$

$$\mathbf{m}_q = \underset{\mathbf{m}_q \in \text{ Cluster } q}{\arg\ \mathrm{m}}\ \sum_{i=1}^{l} d\left(\mathbf{m}_q, \mathbf{x}_{q,i}\right) \quad (12)$$

Repeat until each cluster's centroids and channel vectors remain unaltered.

K-means clustering algorithm:

Input: $K, \mathcal{X}$
Output: $\mathcal{M}$
First stage:
Select first initial centroid $\tilde{\boldsymbol{m}}_1$ *from* $\mathcal{X}$ *randomly*
for $i = 1$ *to* P *do*
$p(\boldsymbol{x}_i) = \frac{D(\boldsymbol{x}_i)}{D(\boldsymbol{x}_i)} \boldsymbol{P} = [p(\boldsymbol{x}_1), p(\boldsymbol{x}_2), \ldots, p(\boldsymbol{x}P)]i$
$= max_i \in P(\boldsymbol{P})\tilde{\boldsymbol{m}}_{t+1} = \boldsymbol{x}_i$
end Repeat 2-10 until Second stage:
$M = \tilde{M}$
for $a = 1$ *to* N *do*
for $a = 1$
$d(a) = \lVert \boldsymbol{x}_i - \boldsymbol{m}_a \rVert^2$
$D = [d(1), d(2), \ldots, d(K)]$
$q = min_{a\in K'}(D)$
Divide x_i *into Cluster q Update the centroids of each cluster:*
$\mathcal{M} = \{\boldsymbol{m}_1, \boldsymbol{m}_2, \ldots, \boldsymbol{m}_K\}$

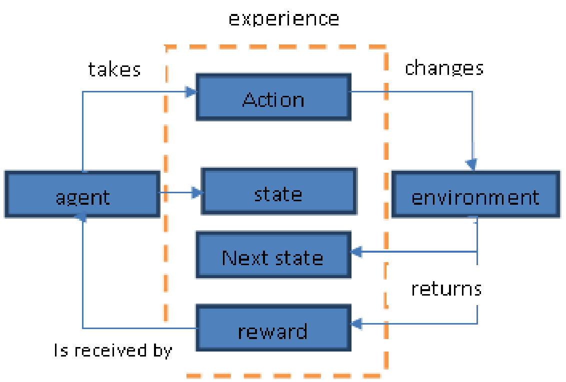

Figure 2. Architecture of RL

The primary elements of the RL architecture and their interactions are shown in Figure 2. The agent, which is the framework's learning component, seeks to learn the best course of action at every given moment t for state st. Value of immediate reward rt that agent receives by taking action at while in state st, as well as anticipated benefits in subsequent states, are connected to how optimal the action at is. Agent interacts with environment, which is an external component. Environment determines value of rt given st and at as well as the condition agent will be in after that, st+1. It is usual to refer to tuple et = "st, at, rt, st+1" as experience. The policy is yet another crucial component of the RL framework. The objective of RL algorithms can be summed up as finding the best course of action to maximise a function of long-term reward. The optimal policy can be discovered using Bellman optimality equations, but our optimization problem cannot be solved using traditional RL techniques. Due to their high memory and processing demands, conventional tabular approaches are limited to low-dimensional discrete state and action spaces. Function approximation techniques must be taken into consideration for both policy as well as long-term reward functions in situations where action as well as state spaces are continuous or arbitrarily large.

4. Results and Discussion

Within a square of 11 km2, this segment is made up of M = 50 APs and K = 30 MSs that are evenly scattered at random. DoF, Spectral Efficiency, Energy Efficiency, SINR, Coverage Area, RL Training Accuracy, and FL Training Accuracy are the simulation parameters taken into account here. Comparative comparison of parameters between the existing and suggested techniques is shown in Table I.

Table I. Comparative Analysis for Parameters between Existing And Proposed Technique

Parameters	**MU-MIMO**	**FL-MEC**	**De_Fed_L-MIMO_K-means_RL**
Spectral Efficiency (bps/Hz)	89	90	92
DOF	88	91	92
Energy Efficiency (%)	91	92	96
Signal to Noise Ratio (dB)	90	89	85
Coverage area	85	88	92
FL training accuracy	89	90	95
RL training accuracy	88	92	98

The above Table I comparative analysis for parameters between existing and proposed techniques in terms of number of users of network and number of edge server by DoF, Spectral efficiency, Energy efficiency, Signal to noise ratio (SNR), Coverage area, RL training accuracy, FL training accuracy.

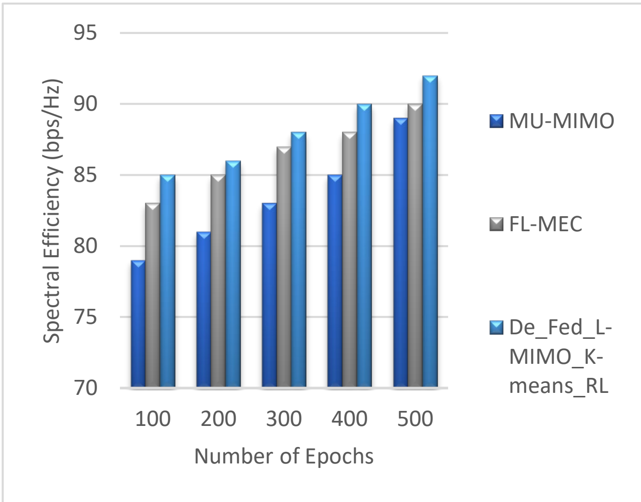

Figure 3. Comparative analysis of spectral efficiency

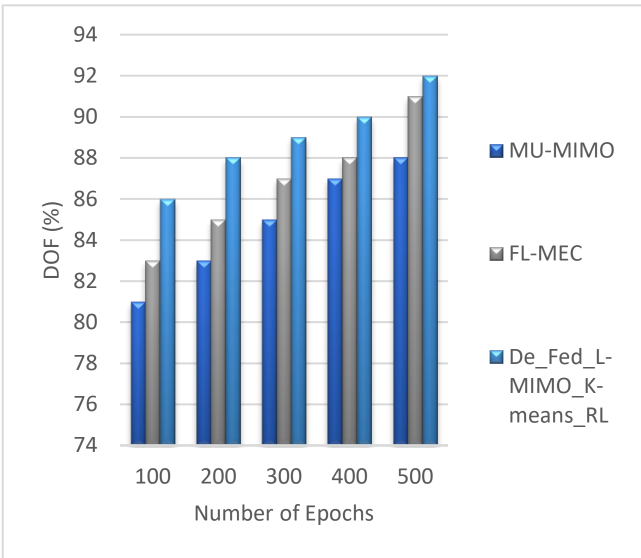

Figure 4. Comparative analysis of DOF

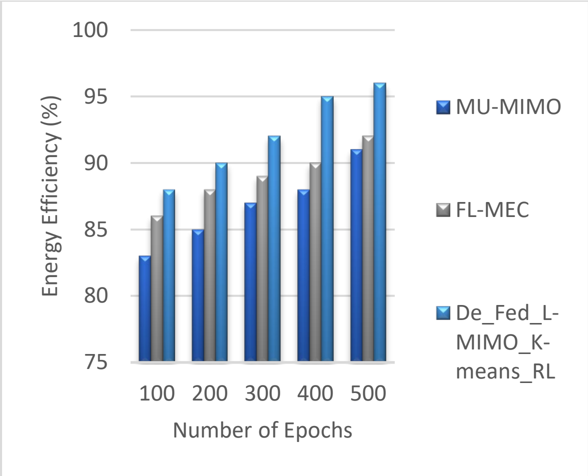

Figure 5. Comparative analysis of Energy efficiency

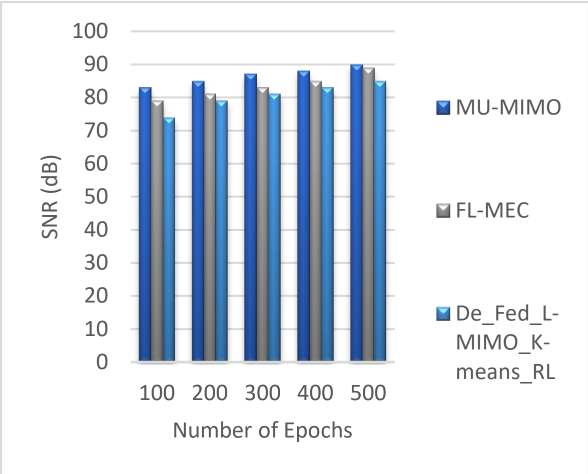

Figure 6. Comparative analysis of SNR

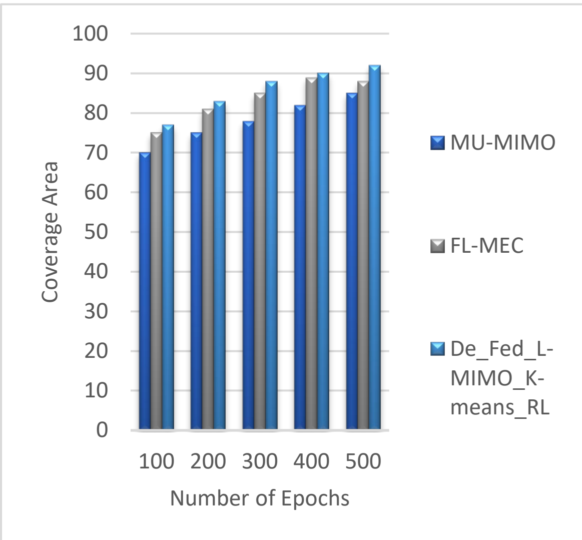

Figure 7. Comparative analysis of Coverage area

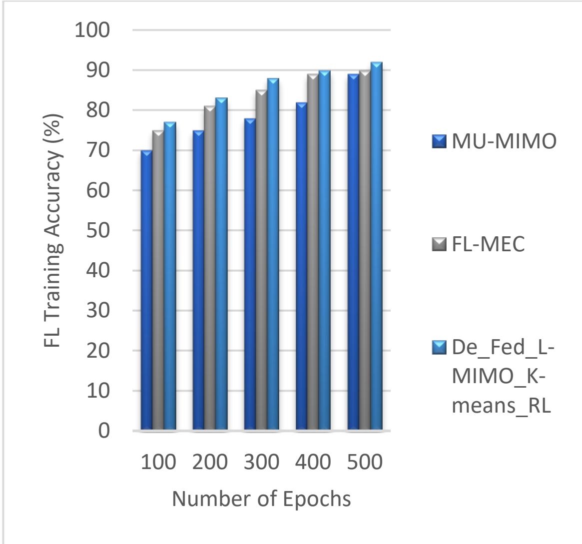

Figure 8. Comparative analysis of FL Training Accuracy

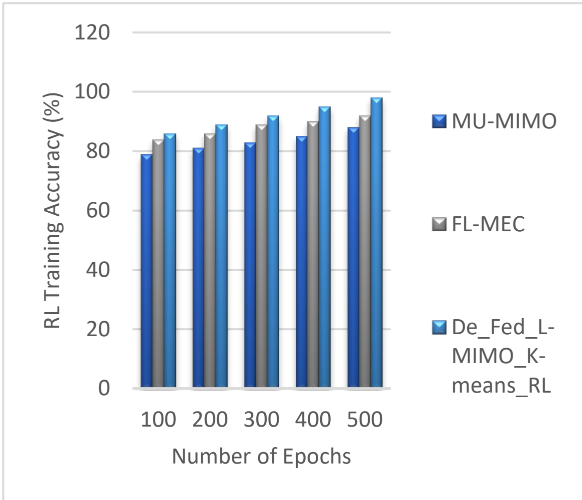

Figure 9. Comparative analysis of RL Training accuracy

The above Figure 3, 4, 5, 6, 7, 8 and 9 shows comparative analysis between proposed and existing techniques. here the proposed technique obtained DoF of 92%, Spectral efficiency of 92%, Energy efficiency of 96%, Signal to noise ratio (SNR) of 85%, Coverage area of 92%, RL training accuracy of 95%, FL training accuracy of 98%; while the existing MU-MIMO obtained DoF of 88%, Spectral efficiency of 89%, Energy efficiency of 91%, Signal to noise ratio (SNR) of 90%, Coverage area of 85%, RL training accuracy of 89%, FL training accuracy of 88%, FL-MEC obtained DoF of 91%, Spectral efficiency of 90%, Energy efficiency of 92%, Signal to noise ratio (SNR) of 89%, Coverage area of 88%, RL training accuracy of 90%, FL training accuracy of 92%. From the above analysis the proposed technique obtained optimal results in edge computing network based on wireless 5G technology using MIMO_federated learning integrated with

Reinforcement neural network when compared with existing technique.

5. Conclusion

This research proposed novel technique in in edge computing network based on wireless 5G technology using MIMO_federated learning integrated with Reinforcement neural network. Here the aim is to enhance the resource allocation by Decentralized Federated learning in multiple user based MIMO (De_Fed_L- MIMO) networks. Then the energy efficiency and channel optimization of the network is carried out using K-means clustering integrated with Reinforcement learning (K-means_RL). Here the experimental analysis is carried out in terms of number of users of network and number of edge server by DoF of 92%, Spectral efficiency of 92%, Energy efficiency of 96%, SNR of 85%, Coverage area of 92%, RL training accuracy of 95%, FL training accuracy of 98%.

Compliance with Ethical Standards

Disclosure of potential conflicts of interest

None

Research involving Human Participants and/or Animals

None

Informed consent

None

Ethical Approval

None

Competing interests

None

Conflict of Interest

None

Funding

None

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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