Green and Intelligent Signal Processing: Deep Learning Approaches for Energy-Efficient MIMO Systems

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ABSTRACT

Due to the massive expansion of wireless applications, the ever-increasing demands for mobile technology, and the development of Internet of Things technology, wireless networks are confronting an increase in data traffic and resource management issues. Due to their capacity for data storage and spectrum efficiency, fifth-generation cellular networks have attracted a lot of interest. In order to meet a variety of user needs, multiple-input multiple-output (MIMO) networks are dependable solutions for data storage and capacity problems. MIMO systems are crucial for achieving revolutionary improvements in energy efficiency (EE) and area throughput. EE is most economical and one of the simplest strategies to fight global warming, energy reduction bills, and improvize competitive performance. EE and area throughput can be greatly enhanced by Deep Learning (DL). In 5G wireless communication systems, it is essential. The suggested model considered the total energy utilization of the circuit elements and the power amplifier of the BS, as well as the user equipment (UE) with a single antenna. In this paper, Green and Intelligent Signal Processing: Deep Learning Approaches for Energy-Efficient MIMO Systems (GISPDL-EEMIMO). The proposed GISPDL-EEMIMO technique undergoes data collection, data preprocessing, feature extraction, and prediction. A set of experiments has been performed to demonstrate the promising performance of the GISPDL-EEMIMO technique. The comparative findings showed that, in terms of distinct measures, the GISPDL-EEMIMO technique outperforms other existing models.

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1. INTRODUCTION

In the context of future 5G wireless communications, multiple-input multiple-output (MIMO) has been viewed as a viable technology due to its ability to achieve improved spectral efficiency and broader bandwidth [1]. To achieve completely digital signal processing in MIMO systems, each antenna typically needs its own radio-frequency (RF) chain, which includes a mixer, high resolution digital-to-analog converter, etc. With the wide range of antennas and high RF chain energy consumption, MIMO would result in prohibitive hardware complexity and energy usage.

Recently, hybrid precoding was introduced to reduce the number of RF chains needed. Its main concept is to break down the digital precoder into a small digital precoder that only needs a few RF chains and a huge analog beamformer that is realized by the analog circuit [2]. The low-rank properties of mmWave channels allow for the spatial multiplexing advantages to be achieved with a small digital precoder, resulting in near-optimal performance for hybrid precoding. Higher data rates and energy efficiency (EE) are constant goals for wireless communication systems due to the quick advancement of mobile communication technologies.

The MIMO technology have become a popular paradigm to support the ongoing popularity of mobile applications. These systems use hundreds of antennas at the BS to effectively serve a million user equipments (UEs) to meet the low-latency, high-rate, and ultra-reliable communication demands of future applications. Both central and dispersed deployments of a significant number of antennas are possible in real-world applications of huge MIMO systems [3].

In the former case, fronthaul is not required because all of the antennas are placed inside a small area. Massive MIMO mitigates UE interference and lowers transmission energy consumption by utilizing channel hardening and advantageous propagation characteristics, enabling higher throughput and increased connectivity. In the latter case, however, separate antennas are linked to a CPU through the fronthaul network, while being geometrically separated.

In 5G, the huge MIMO paradigm holds a lot of promise. It can offer greater spectrum and energy efficiency and contains thousands of antennae. Nevertheless, every antenna, including noise amplifiers and digital-to-analog and analog-to-digital converters, is given a certain frequency. As a result, several active antennas have been used, which increases power consumption. As a result, BS's hardware costs have gone up. The spectrum efficiency can be considerably increased by providing additional antennas for numerous users on the same radio channel frequency. However, the benefits of energy efficiency are diminished by power consumption requirements [4].

Previous methods have demonstrated that reducing the low resolution caused by power consumption has drawbacks. The dynamic nature of WSN, in particular allocation of resources in huge MIMO, is what drives our research. As the need for wireless transmission that is fast, dependable, and energy-efficient (EE) grows, resource allocation optimization takes center stage. In connection with complicated situations that require both continuous and discrete decision-making makes this difficulty even more apparent.

Due to its direct impact on operational costs and sustainability, EE has emerged as a crucial statistic in contemporary WSN. It is a challenging issue that requires sophisticated solutions to achieve high EE while guaranteeing smooth power allocation (PA) and user association. Therefore, meeting this urgent need for wireless networks that are more ecological and efficient is what drives us. We are motivated by the opportunity to significantly improve customer enjoyment, energy conservation, and resource management [5].

Emerging machine learning (ML) is therefore a useful tool for resolving these kinds of challenging multi-objective issues. The best branch of machine learning (ML) for resolving non-convex problems. The three main components of the suggested solution—agents, reward, and action—allow the self-learning capabilities from the surroundings in RL-based optimization techniques. We used a DL algorithm in this study to present a new technique. The following are this paper's primary contributions:

- Our study offers a sophisticated solution to the user association and PA problems, with the main goal being to maximize EE in the framework of a huge MIMO system. By making EE our main objective, we tackle a crucial component of contemporary WSN, emphasizing the usefulness of our study.
- According to the simulation results, the suggested GISPDL-EEMIMO strategy outperforms the other approaches.
- By using system simulations, we show that the suggested method converges steadily and that, as the number of network users rises, it performs more energy efficiently than the traditional MIMO.

1.2 MIMO System Model

Various antennas are used at both the transmitter and the receiver to broadcast the signals [6] in a MIMO system. Let $\mathrm{N_t}$ and $\mathrm{N_r}$ be the amount of $\mathrm{T_x}$ antennas and receiving ($\mathrm{R_x}$) antennas, and $\mathrm{s} \in \mathcal{A}$ be an M-ary modulated symbol. Then, in the $(\mathrm{N_r} \times \mathrm{N_t})$ MIMO systems, a vector of several symbols $\mathrm{s} \in \mathbb{C}^{1\times \mathrm{N_t}}$ sent simultaneously can be written as

$$\mathrm{s} = [\mathrm{s_1}, \mathrm{s_2}, \cdots\ \mathrm{s_{N_t}}]^{\mathrm{T}} \tag{1}$$

$$\mathrm{r} = \begin{Bmatrix} \mathrm{r_1} \\ \mathrm{r_2} \\ \vdots \\ \mathrm{r_{N_r}} \end{Bmatrix} = \begin{Bmatrix} \mathrm{h_{1,1}} & \mathrm{h_{1,2}} & \mathrm{h_{1,N_t}} \\ \mathrm{h_{2,1}} & \mathrm{h_{2,2}} & \mathrm{h_{2,N_t}} \\ \vdots & \vdots & \vdots \\ \mathrm{h_{N_r,1}} & \mathrm{h_{N_r,2}} & \mathrm{h_{N_r,N_t}} \end{Bmatrix} \begin{Bmatrix} \mathrm{s_1} \\ \mathrm{s_2} \\ \vdots \\ \mathrm{s_{N_t}} \end{Bmatrix} + \begin{Bmatrix} \mathrm{n_1} \\ \mathrm{n_2} \\ \vdots \\ \mathrm{n_{N_r}} \end{Bmatrix}, \tag{2}$$

$$\mathrm{r} = \mathrm{Hs} + \mathrm{n} \tag{3}$$

Where the additive white Gaussian noise samples at $\mathrm{j^{th}}$ receiver antenna are denoted by $\mathrm{s} \in \mathbb{C}^{1\times \mathrm{N_t}}$ and $\mathrm{n} \in \mathbb{C}^{\mathrm{N_r}\times 1}$. With variance N0, represented as CN(0, N0), we assume that the noise is equally distributed and independent.

In this paper, Green and Intelligent Signal Processing: Deep Learning Approaches for Energy-Efficient MIMO Systems (GISPDL-EEMIMO). The proposed GISPDL-EEMIMO technique undergoes data pre-processing, feature extraction, and prediction. A set of experiments has been performed to demonstrate the promising performance of the GISPDL-EEMIMO technique. The comparative findings showed that, in terms of distinct measures, the GISPDL-EEMIMO technique outperforms other existing models.

2. RELATED WORKS

Sahu et al [7] examine the issue of designing relay precoders that are energy efficient for MIMO cognitive relay networks (MIMO-CRNs). Traditionally, computationally costly optimization techniques are used to handle this non-convex fractional programming problem. In this work, we suggest a method for computing an approximation answer that is based on DL. In particular, an offline computed optimal solution is applied for training a deep neural network (DNN). The suggested plan is divided into three stages: online deployment, offline training, and offline data generation. The suggested technique is appropriate for real-time implementation since the numerical results demonstrate that the suggested model offers equivalent performance at a substantially lower computational complexity than the traditional algorithm.

Sharma and Yoon [8] utilize the Parameterized DQN (PD-DQN), a multi-agent DRL technique, to tackle the difficult issues of PA and user association in huge (M-MIMO) communication networks. Our method addresses a multi-objective optimization problem in M-MIMO networks that seeks to optimize network utility while satisfying strict QoS criteria. We present a unique multi-agent DQN framework to tackle these problems' non-convex and nonlinear characteristics. We can learn a near-optimal policy thanks to this framework, which defines a huge action space, state space, and reward functions. Simulation findings show that our technique outperforms both RL and conventional DQN methods. In particular, we demonstrate that our method performs better in terms of convergence rate and ultimate performance than conventional DQN methods. Furthermore, when it comes to solving largescale multi-agent problems in M-MIMO systems, our solution outperforms DQN methods by 72.2% and the RL method by 108.5%.

Gupta et al. [9] suggest a LSTM based approach that increases energy efficiency by making decisions based on dynamic wireless network information, channel complexity, and RIS energy harvesting. The suggested LSTM model predicts the ideal RIS configuration for every transmission after being trained in a real-time setting. These transmissions are intended for users spread over different areas of the respective wireless network. The system model is constructed using the LSTM model and Adam optimizer, and its robustness and energy efficiency are investigated. According to the outcomes of several simulations, the LSTM framework increases the RIS elements from 9 to 25 while boosting energy efficacy to 35.42%. Furthermore, the model can attain a net data rate of over 100 bps/Hz.

Hojatian et al. [10] examine the issue of optimizing the EE of HBF transmitters with fully digital precoders (FDP). We start by suggesting an energy model for various beamforming configurations. We then construct the transmitter configuration for FDP and HBF using a self-supervised learning (SSL) approach based on the suggested energy model in order to maximize the EE. The suggested deep neural networks can adjust to varying numbers of active users while offering various trade-offs between energy usage and spectral efficiency. According to simulation results, even when trained with faulty CSI, the suggested solutions can outperform traditional approaches in terms of EE. Additionally, we demonstrate that compared to traditional approaches, the suggested solutions are simpler and more resilient to noise.

Sahu et al. [11] investigate the challenge of creating an EE joint precoder for MIMO-CRN at both the source and the relay. In order to discover the best solution for such nonconvex fractional programming problems, existing optimization techniques usually have a high computational complexity. Unlike previous research, this paper uses a DNN to create the joint precoders utilizing a data-driven technique. The numerical findings show that, as compared to the traditional optimization-based methodology, this method offers a comparable performance at a much reduced computational cost. Additionally, it is demonstrated that the suggested method is very resilient to changes in the channel statistics, making it appropriate for real-time deployment.

DEVIPRIYA [12] For downlink MIMO-NOMA systems, the PA problem was examined using both non-DL and DL techniques. With this realization, the non-DL approach is used to address the problem first, and the proposed PASR (PA based on shifting additional resources) strategy resolves it. Two distinct assumptions are used to study this scheme: variable inter-cluster power (V-PASR) and fixed inter-cluster power (F-PASR). Ultimately, a ML approach was put up to address the issue of power distribution. For PA, an EE-DNN model was suggested in order to lower the complexity and latency of the previously discussed issue. The efficiency of the suggested EE strategies is confirmed by extensive simulation results. The suggested F-PASR and V-PASR algorithms were shown to perform better than the traditional approach. Additionally, it was confirmed that while deep learning-based frameworks require less computation time, they perform somewhat worse than non-deep learning methods.

Li et al. [13] examines a cell-free MIMO (CF-mMIMO) system and develops a two-stage energy efficiency (EE) optimization algorithm based on iterative search for the system's uplink communication. Reliability is given top priority in the first step to guarantee that all users satisfy the URLLC's latency and reliability standards. When URLLC is satisfied, the second stage optimizes the EE. We further suggest a convolutional neural network architecture (RACNN) to approximate an ideal resource allocation strategy and to realize the real-time and stable output, taking into account that iterative search algorithms have a variable number of iterations and a large computational overhead. Deep user correlations are extracted from the global channel features via this structure. Weight loss adaptation and multitask learning techniques are used to increase the model's rate of convergence. In addition, we use deep transfer learning to modify RACNN parameters to account for the possibility of dynamic communication circumstances, which lowers the overhead of training time and the requirement for training samples. Lastly, experimental simulations are used to verify the effectiveness of deep transfer learning and the suggested algorithm, RACNN.

3. PROPOSED METHODOLOGY

In this work, we introduce a GISPDL-EEMIMO approach. The proposed GISPDL-EEMIMO technique undergoes data preprocessing, feature extraction, and prediction. The overall architecture of the GISPDL-EEMIMO model is shown in Figure 1.

3.1 Data Preprocessing

In EE-MIMO systems, normalization is a popular data pre-processing method for scaling input signal values for reliable and effective deep learning model training [14]. Z-score normalization (Eq. 4) is used to normalize each segment in order to lessen the impact of any outlier samples in that segment.

$$Z_i = \frac{X_i - \overline{X}}{S} \qquad (4)$$

Z_i is the Z-score value of thei^{th} sample X_i for a given segment, and $\overline{X}$ and S are the sample mean and standard deviation for that segment.

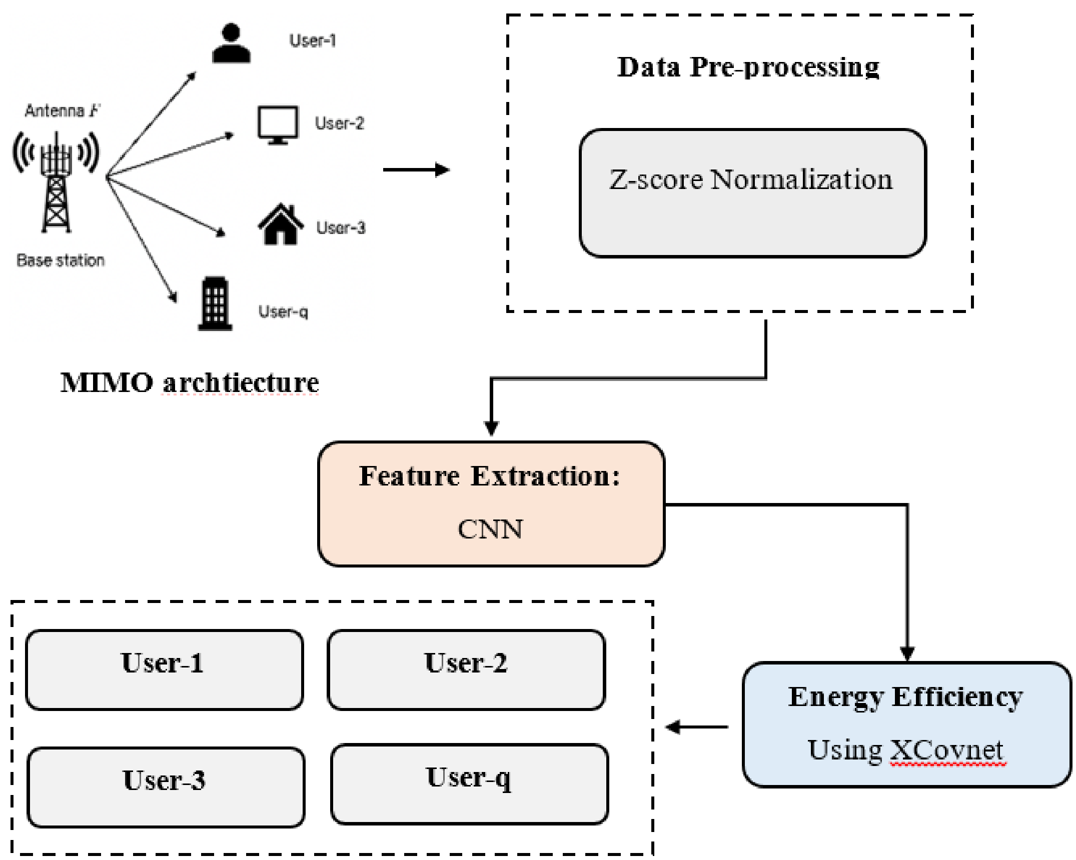

Figure 1. Overall architecture of the GISPDL-EEMIMO model

3.2 Feature Extraction Based CNN

CNN uses deep learning to provide intelligent [15] and EE processing by extracting important spatial information from MIMO signal data. A common FFNN, the classic CNN, is utilized extensively in speech detection, image recognition, and other domains due to its strong feature extraction abilities. An input, a convolutional, a pooling, and a fully connected layers typically make up a conventional CNN. The convolutional layer remove noise and adaptively extract the features of the input dataset.

In turn, the relevant convolution kernel is chosen to handle the input data. Different features are represented by different convolution kernels. By combining several convolution kernels, the convolutional neural network often improves the model's feature extraction capabilities and produces multi-layer data with defect features. The formula for convolution is:

$$x_j^l = f\left(\sum_{i\in M_j} x_i^{l-1} \cdot w_{ij}^l + b_j^l\right) \tag{5}$$

In Eq. (5), w_{ij}^l and b_j^l are the weight and bias matrices, f refers to the activation function, the part of the input data that has to be convolved is represented as $x_{i^{l-1}}$, the dimension of the input data is denoted by M_j, and the number of layers in the network is denoted as l.

$$\mathrm{ReLU}(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{6}$$

The pooling layer is otherwise known as the down-sampling layer. The pooling layer is frequently employed as the mean and the max pooling function. The convolution kernel recovers the average or maximum value of the associated area by iteratively navigating through the target data.

As a result, the pooling layer's job is to reduce the dimensionality of the convolution layer's output data while extracting its key characteristics. The largest pooling function is selected in this model. It is expressed as:

$$x_j^l = f(\beta_j^l \cdot \mathrm{down}(x_j^l) + b_j^l) \quad (7)$$

3.3 Energy Efficiency Using XCovNet

Energy efficiency is seen as a key performance metric in MIMO, particularly as the need for high-speed data and reliable large-scale connectivity grows. Moreover [16], MIMO technology, which increases the robustness of wireless communication by enabling multiplexing and spatial diversity, uses several antennas at both the transmitter and the receiver. XCovNet is a deep learning network that learns cross-covariance patterns between sent and received signals in order to predict channel state information (CSI) in MIMO systems. XCovNet receives the parameter with dimension $R \times C \times 3$ as input. The foundation of XCovNet is the Inception architecture. By utilizing separable convolutions (Conv), the XCovNet technique is regarded as an effective and efficient model that can be used without reducing performance rate. The three blocks that make up this network are the Conv block, the Depthwise Separable Conv block, and the completely linked layer block. Conv layers are used by the Conv block of XCovNet, and the layer after the input generates Conv kernels for creating different feature maps that display the features of the input data.

All of the Conv kernels are distributed over each input data region throughout the feature map construction process. Several Conv layers are used to obtain the feature map's relative results. The formula for calculating the feature map $M_{v,g,\eta}^{w}$ is provided below when the feature value (v, g) of a η^{th} feature map of w^{th} layer.

$$M_{v,g,\eta}^{w} = G * p_{\eta}^{w} * H_{v,g}^{w} + \theta * p_{\eta}^{w} \quad (8)$$

The input patch on layer w at the $(v, g)^{th}$ 1ocation is represented by $H_{v,g}^{w}$ in this instance, the weight vector is shown by $G * p_{\eta}^{w}$, the generated feature maps are specified by $M_{v,g,\eta}^{w}$, and the bias values of the η^{th} feature map and w^{th} 1ayer are shown by $\theta * p_{\eta}^{w}$.

Additionally, the shared kernels $G * p_{\eta}^{w}$ are used to create the feature maps $M_{v,g,\eta}^{w}$. Among the many advantages of the weight distribution system is its reduced complexity. Following the Conv layer, feature maps take advantage of the activation and max pooling layers. The parametric PreLU, a generalized rectified unit activation function with a negative slope, is employed here and is represented as follows:

$$\beta(d_v) = \begin{cases} d_v, \text{if } d_v > 0 \\ T_v d_v, \text{if } d_v \leq 0 \end{cases} \quad (9)$$

The activation function, which achieves faster convergence with fewer overfitting risks, is used to identify nonlinear features, while the max-pooling layer is used to reduce the dimension of the feature map.This block is an example of a Conv technique that operates in both space and depth. Here, two phases—depth-wise and pointwise Conv—are included to make the Conv operation simpler.

These Conv are typically used by DL frameworks when filters cannot be broken down into smaller ones. Additionally, a kernel is used by the pointwise Conv, and it repeats over each point.

Two Conv layers are used to mine the features after an input of dimension R × C × 3 is sent to the Conv block. Additionally, each Conv layer has PreLU activation, padding, and two distinct Conv2D layers. To improve convergence, the activation is normalized in batches, and the max pooling layer is used to reduce the spatial dimension. Furthermore, for regularization, a dropout layer with a 0.2 rate is used. Furthermore, overftting issues are avoided by using the dropout layer. After that, a fatten layer is used to transform the 3D tensor into a 1D vector. Furthermore, dense is considered the final layer, after which the class probabilities are converted into outputs by utilizing the sofmax activation function. Additionally, this network maintains computation efficiency while capturing the important information.

4. RESULTS AND DISCUSSIONS

The simulation outcomes of GISPDL-EEMIMO are demonstrated in this section. In this case, the BS transmits the signal to three header nodes, which subsequently disseminate it to every piece of UE below it. It is demonstrated how to investigate GISPDL-EEMIMO for the Rayleigh channel by varying the number of users. The user and throughput graph. With 10, 20, 30, and 40 repetitions, GISPDL-EEMIMO achieves a throughput of 551.262, 515.922, 533.26, 485.206, and 497.922 Mbps for 300 users, correspondingly. The analysis of GISPDL-EEMIMO based on the sum rate is shown in Figure 4. For 100 users, the cumulative rate as determined by GISPDL-EEMIMO is 269.930 Mbps for 10 iterations, 236.630 Mbps for 20 iterations, 221.630Mbps for 30 iterations, and 230.630 Mbps for 40 iterations. The analysis of GISPDL-EEMIMO based on energy efficiency is indicated in Figure 2. The parameter settings used in the GISPDL-EEMIMO approach are illustrated in Table 1.

With iterations 10, 20, 30, and 40, GISPDL-EEMIMO achieved energy efficiency of 74.943kbits/joule, 63.102kbits/joule, 55.014 kbits/joule, 31.012 kbits/joule, and 39.021 kbits/joule for 200 users. The GISPDL-EEMIMO throughput-based analysis is indicated. For 200 users with 10, 20, 30, and 40 iterations, GISPDL-EEMIMO achieves throughputs of 497.922 Mbps, 485.206 Mbps, 533.26Mbps, and 551.262Mbps. GISPDL-EEMIMO's sum rate, when 400 users are taken into account, is 236.630 Mbps with 10 iterations, 221.63 Mbps with 20 iterations, 230.630 Mbps with 30 iterations, and 269.930 Mbps with 40 iterations. With 10, 20, 30, and 40 iterations, GISPDL-EEMIMO computed an energy efficiency of 51.632 kbits/joule, 60.238 kbits/joule, 64.752 kbits/joule, and 72.542 kbits/joule for 300 users.

Table 1. Parameter settings in GISPDL-EEMIMO approach

PARAMETERS	VALUES	PARAMETERS	VALUES
Radius of the network area	400m	Number of BS	1
Number of UE	150	Max connected BS per UE	2
Number of header nodes	4	Total simulation time	9s
Time step	1s		

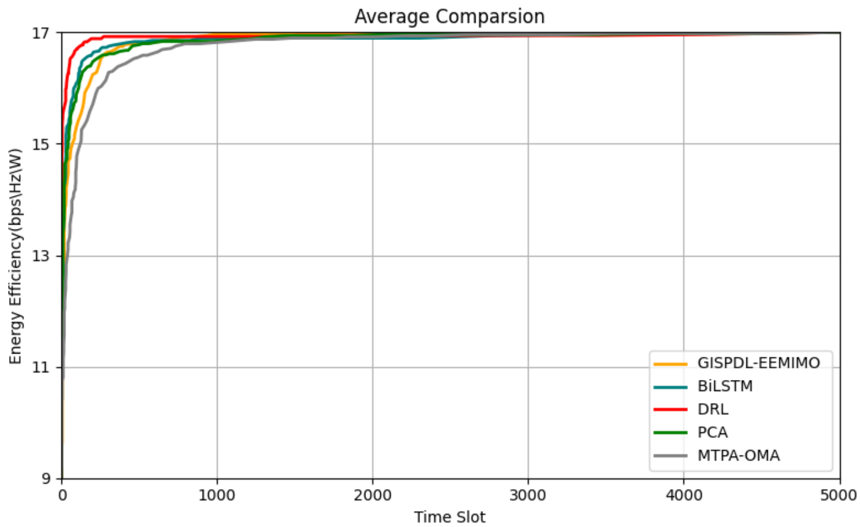

Figure 2. Average EE comparison of GISPDL-EEMIMO with other existing approaches

Since the suggested GISPDL-EEMIMO offered superior learning performance in our simulations, we first assess its convergence at a fixed learning rate of 0.01. To find the number of TSs needed for our frameworks to find the best PA policy, we fix the location of every user. For two frameworks, the loss function value falls and tends to a stable value within 200 TS, as seen in Figure 3. The value is sufficiently modest to estimate the Q value with accuracy.

Then, using various PA strategies, we contrast the algorithms that have been suggested for the random moving system. To make the comparison easier to understand, it should be noted that all findings are averaged using a moving window of 100 TSs. We examine the performance of our GISPDL-EEMIMO based frameworks for the sum EE maximization goal.

We examine averaged sum EE performance in 5000 TSs with varying transit power constraints. While the BiLSTM model marginally increases and continues to drop since it always requires full power for the signal transmission, the outcomes of GISPDL-EEMIMO frameworks grow and trend to stable values as the maximum power increases, as illustrated in Figure 2. This is due to the fact that our algorithms can dynamically distribute the power based on the communication conditions to optimize the cumulative EE regardless of how pmax changes, as long as the data rate requirement is met. And we verify the averaged energy efficiency versus power limitation in Figure 4. The EE variation with the minimum required date rate enhanced performance of the GISPDL-EEMIMO techniques over other approaches.

Table 2. Comparative discussion of GISPDL-EEMIMO

METRICS	**GISPDL-EEMIMO**	**BiLSTM**	**DRL**	**PCA**	**MTPA-OMA**
Throughput (Mbps)	551.262	515.922	533.26	485.206	497.922
Sum rate (Mbps)	269.930	236.630	221.630	230.630	242.610
Energy efficiency (kbits/joule)	74.943	63.102	55.014	31.012	39.021

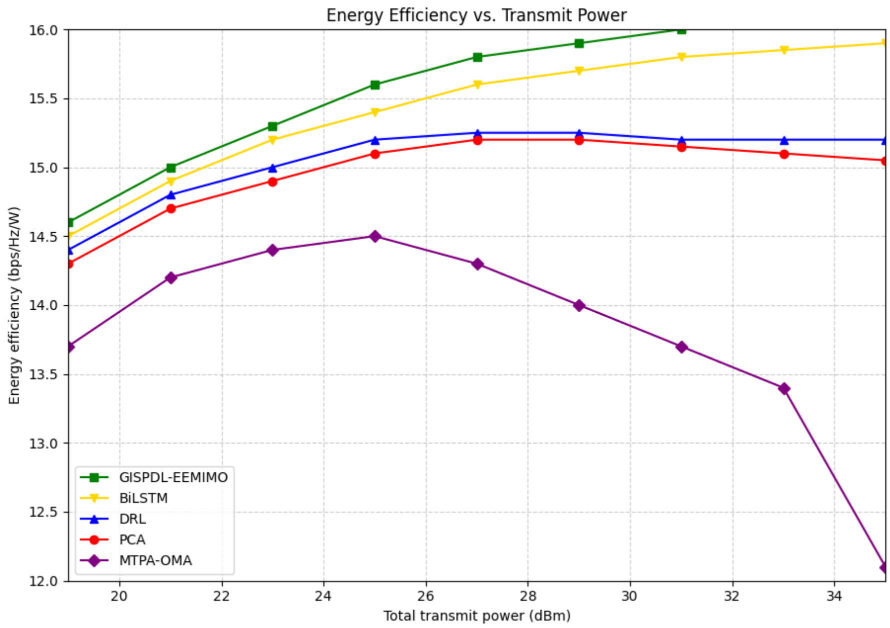

Figure 3. EE Vs transmit power of GISPDL-EEMIMO technique with other approaches

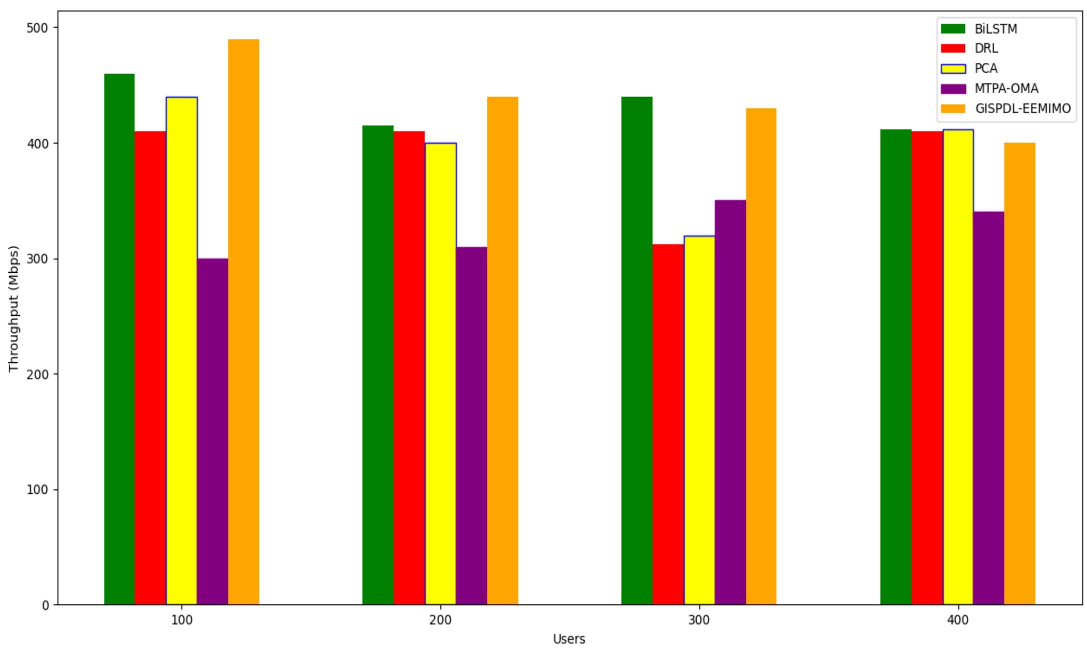

Figure 4. Performance measure of GISPDL-EEMIMO throughput with other approaches

The performance measure of GISPDL-EEMIMO throughput with other approaches is shown in Figure 4. Based on the current channel circumstances in each TS, the GISPDL-EEMIMO-based frameworks may continuously control and dynamically select each user's transmit power. In particular, the GISPDL-EEMIMO framework's averaged sum EE value over all 5000 TSs is 25.47% greater than the PCA method, whereas the DRL framework's values are 18.38% higher. The averaged cumulative EE value for the BiLSTM framework across all 5000 TSs is 22.27% higher than the MTPA-OMA technique, while the MDPA framework's values are 15.3% higher. More importantly, using full power for transmission is wasteful and wastes energy because it lowers the system's EE as long as all users' data rate requirements are met. This further demonstrates how crucial PA is to enhancing the GISPDL-EEMIMO system's performance. Additionally, we confirm that the GISPDL-EEMIMO algorithms outperform other approaches in terms of performance.

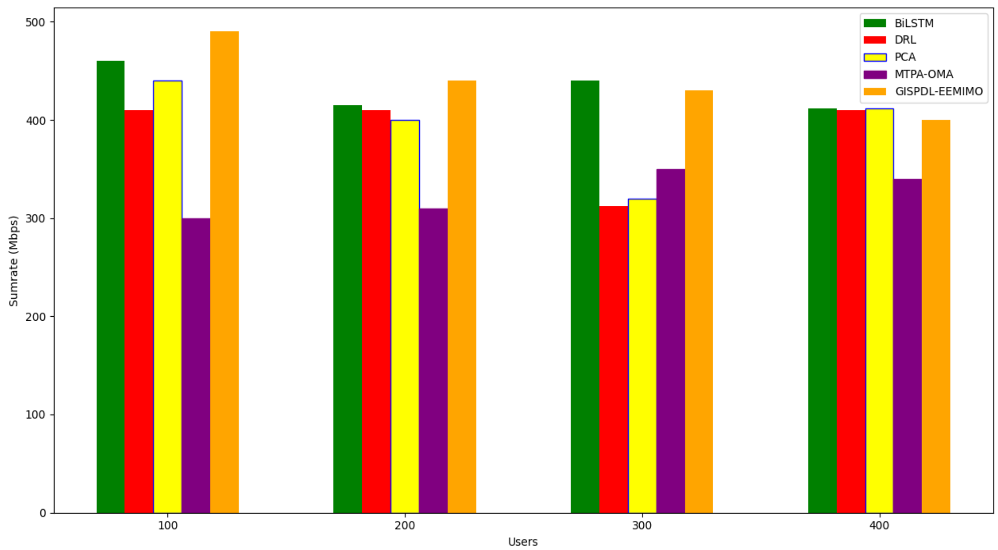

Figure 5. Performance measure of GISPDL-EEMIMO sum rate with other approaches

The analysis of GISPDL-EEMIMO based on the sum rate with alternative techniques is shown in Figure 5. The GISPDL-EEMIMO total rate, when 400 users are taken into account, is 286.564 Mbps with 10 iterations, 256.576 Mbps with 20 iterations, 268.964 Mbps with 30 iterations, and 244.26 Mbps with 40 iterations. The GISPDL-EEMIMO technique achieved the maximum sum rate compared with other approaches.

5. CONCLUSIONS

In this paper, Green and Intelligent Signal Processing: Deep Learning Approaches for Energy-Efficient MIMO Systems (GISPDL-EEMIMO). The proposed GISPDL-EEMIMO technique undergoes data pre-processing, feature extraction, and prediction. A set of experiments has been performed to demonstrate the promising performance of the GISPDL-EEMIMO technique. The comparative findings showed that, in terms of distinct measures, the GISPDL-EEMIMO technique outperforms other existing models.

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