An Efficient Channel Prediction Using Artificial Neural Network Deep Learning Technique in Cognitive Radio

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***Abstract*— Efficient channel prediction plays a critical role in optimizing the performance of cognitive radio (CR) networks, where spectrum availability is dynamically utilized. This paper presents a novel approach for channel prediction using Artificial Neural Networks (ANNs), a deep learning technique, to enhance the adaptability and efficiency of cognitive radio systems. The primary objective is to predict the channel state with high accuracy, enabling the CR network to adapt to the varying spectrum conditions and improve overall communication quality. By employing a multi-layer perceptron (MLP) architecture, the model is trained on past channel state information (CSI) to forecast future channel conditions. The study evaluates the prediction performance under various real-world conditions, such as noise, interference, and channel fading. Simulation results demonstrate that the ANN-based prediction model outperforms traditional methods, achieving higher accuracy and faster adaptation, leading to enhanced spectral efficiency and reduced interference.**

***Keywords*— Cognitive Radio, OFDM, MATLAB, Power.**

I. INTRODUCTION

Cognitive Radio (CR) is an intelligent wireless communication system that has emerged as a promising solution to address the challenges of spectrum scarcity. Unlike conventional wireless systems, which are statically assigned to specific frequency bands, CR networks are designed to dynamically access underutilized spectrum bands. This dynamic spectrum access (DSA) mechanism relies on efficient channel prediction to ensure optimal spectrum utilization while minimizing interference to primary users (PUs). Channel prediction is the process of estimating future channel conditions based on historical data, enabling the cognitive radio network to make informed decisions about spectrum access.

The efficiency of channel prediction directly impacts the performance of CR networks. Accurate prediction of channel states enables the secondary users (SUs) to avoid interference with PUs, select the best available spectrum bands, and adapt to changing network conditions. Traditional channel prediction techniques, such as time-series models and statistical methods, have limitations in capturing the complex, nonlinear relationships inherent in wireless channels. These methods often struggle with accurately predicting channel variations due to factors like fading, noise, and interference.

In recent years, deep learning techniques, particularly Artificial Neural Networks (ANNs), have gained significant attention in the field of cognitive radio due to their ability to model complex nonlinear relationships and extract high-level features from large datasets. ANN-based models have shown promising results in various prediction tasks, including time series forecasting and classification. By leveraging historical channel state information (CSI), ANNs can predict future channel conditions with high accuracy, thereby enabling more efficient spectrum management.

This paper explores the application of ANN-based models for efficient channel prediction in cognitive radio networks. The proposed model utilizes a multi-layer perceptron (MLP) neural network, which is trained on past CSI to predict future channel states. The model's performance is evaluated under various network scenarios, considering factors such as noise, interference, and fading. Through extensive simulations, the study demonstrates that the ANN-based prediction model significantly outperforms traditional techniques in terms of prediction accuracy and computational efficiency.

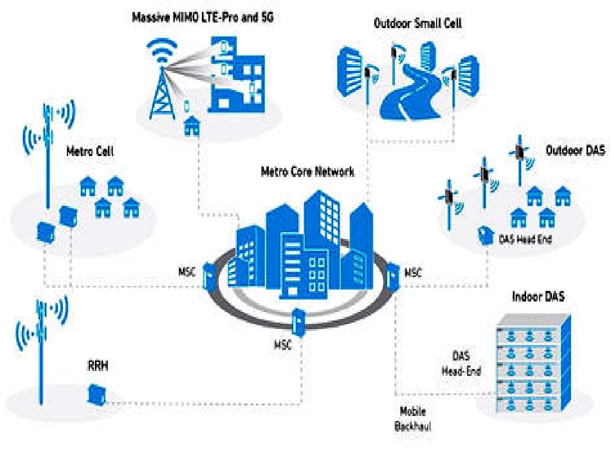

Figure 1: Wireless Infrastructure

The ability of ANNs to learn from large datasets and generalize from past observations makes them highly effective for dynamic environments, such as cognitive radio networks. The proposed ANN model in this study is specifically designed to capture the time-dependent and spatial correlations within the channel states, allowing the system to forecast future conditions accurately. By utilizing multiple hidden layers, the model is capable of identifying complex patterns that traditional models might miss. Moreover, the adaptability of deep learning techniques enables the model to handle non-stationary environments, where the channel conditions change rapidly due to mobility, varying interference, and other environmental factors. This makes ANN an ideal candidate for predicting channel conditions in real-time, ensuring seamless spectrum allocation for secondary users.

In addition to improving prediction accuracy, the implementation of ANNs also contributes to the overall efficiency of cognitive radio systems by reducing the computational load. Unlike traditional methods, which may require extensive real-time computation or iterative processes, the trained ANN model can provide quick predictions once the training phase is completed. This aspect is critical in the context of real-time spectrum management, where fast decision-making is essential for minimizing latency and maximizing throughput. By enabling quick and reliable channel predictions, ANNs allow cognitive radios to make proactive decisions about spectrum handoff, power control, and interference mitigation. As a result, the integration of deep learning techniques into cognitive radio systems can significantly enhance the performance and scalability of modern wireless communication networks.

II. PROPOSED MODEL

The contribution of proposed research work is as followings-

- To make a 5G Large-Scale MIMO System model in MATLAB software.
- To assign more number of transmitter and receiver antenna as a MIMO system.
- To propose support detection (SD)-based channel estimation scheme with reliable performance and low pilot overhead.
- To measure performance parameters and optimize the better value with channel estimation.

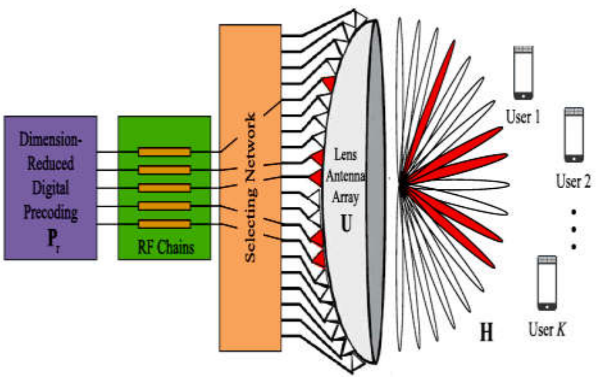

Figure 2: mm-wave massive MIMO with lens antenna array

Wireless mm-wave Massive MIMO with Lens Antenna Array the conventional channel in the spatial domain can be transformed to the beamspace channel by employing a carefully designed lens antenna array as shown in figure 2. Essentially, such lens antenna array plays the role of a spatial DFT matrix U of size N × N, which contains the array steering vectors of N orthogonal directions (beams) covering the entire space.

The basic steps of methodology is as followings-

- First design an adaptive selecting network for mm-wave massive MIMO systems with lens antenna array to formulate the beamspace channel estimation problem as a sparse signal recovery problem.
- Now apply support detection (SD)-based channel estimation scheme with reliable performance and low pilot overhead.
- This allows a system to have better performance in a fading environment.
- Then, by utilizing the special structural characteristics of mm-wave beamspace channel, we propose a SD-based channel estimation scheme with low pilot overhead.
- Millimeter-wave (mm-wave) massive MIMO with lens antenna array can considerably reduce the number of required radio-frequency (RF) chains by beam selection.
- However, beam selection requires the base station to acquire the accurate information of beamspace channel.

ANN based Steps-

The process of using an Artificial Neural Network (ANN) for channel prediction in a Cognitive Radio (CR) network begins with data collection. This step involves gathering historical channel measurements from different locations within the CR deployment area, ensuring a diverse range of channel conditions is captured. It includes important parameters like frequency bands, signal strength, and signal-to-noise ratios, all of which are crucial for building an accurate prediction model. The dataset must span a long enough time period to cover various environmental and network conditions.

Once the data is collected, the next step is data preprocessing. This involves cleaning the data by removing outliers and noise to ensure its quality. After cleaning, the data is normalized or standardized to bring all features to a similar scale, which is essential for efficient training of the neural network. The relevant features are then extracted, such as historical channel states, environmental factors like weather, network traffic, and information regarding primary user activity and interference. This feature extraction helps focus the model on the most significant variables that affect the channel state.

After preprocessing, the data is split into training, validation, and test sets. The training set is used to teach the neural network, while the validation set helps fine-tune hyperparameters, and the test set is used to evaluate the model's performance. A suitable deep neural network architecture is designed, including an input layer with neurons corresponding to the selected features, hidden layers with activation functions like ReLU, and an output layer predicting the channel state. The model is trained using backpropagation and gradient descent. During training, hyperparameters are fine-tuned, and regularization techniques like dropout are applied to prevent overfitting. The final model is evaluated using performance metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), comparing predicted values with actual measurements to assess its accuracy.

III. SIMULATION RESULTS

The implementation of the proposed algorithm is done over MATLAB 9.4 (R2018a)

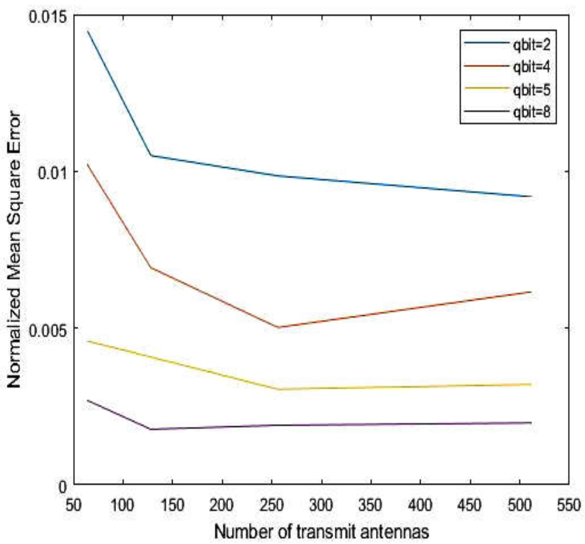

Figure 3: NMSE vs No of transmitter antenna

Figure 3 shows the Channel was constructed according to multi transmitter (M) and it is directly related NMSE so, we can see the above graph the relation of NMSE and Mt. While increasing the Mt, NMSE is decreasing as it is expected. Also, after 256 transmitter antennas number NMSE is keeping the same NMSE value so 128 is optimum number of antennas.

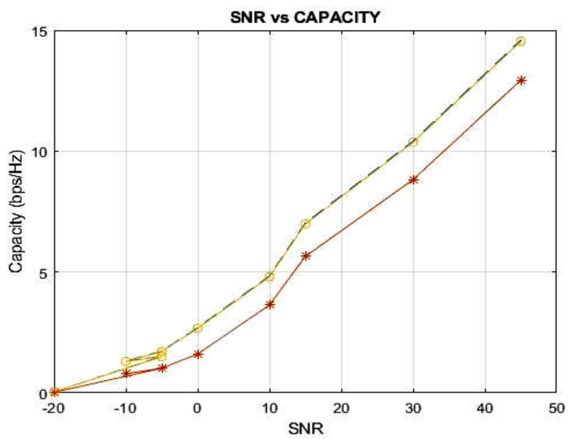

Figure 4: Capacity vs SNR

Figure 4 shows the graph which is provided that the increased SNR values capacity is increasing as an expected. The estimated channel capacity is shown with red line and its capacity less than perfect and error channel's. Also, perfect channel capacity is higher than the error channel's because error decreases the capacity of the channel.

Table 1: Result Comparison

Sr No	Parameters	Previous Work	Proposed Work
1	Method	Time and Spatial Correlation	Support Detection
2	Modulation	Q-QAM	M-QAM
3	SNR	0.9 – 10 dB	40 dB
4	NMSE	-1 dB	10^{-1} dB

Table 1 is showing comparison table of proposed and previous work in terms of modulation scheme, SNR and NMSE. The optimized SNR value is 40dB, while previously it is 0.9 to 10dB. The NMSE value is 10^{-1} dB while previously it is -1dB.Therefore, simulated result shows that the proposed approach gives significant better results than existing work.

IV. CONCLUSION

The performance study of this research demonstrates that the suggested SD-based channel estimation technique can identify the support of sparse beamspace channels with more accuracy than traditional CS algorithms. The complexity study indicates that SD-based channel estimation has low complexity, similar to that of the LS technique. Simulation findings confirm that the proposed SD-based channel estimation method significantly outperforms existing systems in terms of NMSE performance, especially in low SNR conditions. This enhances the appeal of mm-wave huge MIMO systems using lens antenna arrays.

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