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# IRS Based Wireless Channel Estimation Using Deep Learning

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**ABSTRACT**
A channel's quality can be raised by utilizing a programmed reflecting surface with passive components that is designed to send a beam of reflection to the receiver from the incident signal. In this study, we employ an orthogonal frequency division multiplexing (OFDM) system with a changeable reflecting surface, two states for each element of the Intelligent Reflecting Surface (IRS). The IEEE Signal Processing Cup 2021 has offered the simulation setup and dataset for various user equipment (UEs). In order to get better signal datarates, we want to employ a different methodology like Deep Learning technique and make enhancements. Different IRS configurations have different received power values and mean-square errors.

The received signal power given an IRS configuration is predicted using Convolutional Neural Network and compared by plotting with the actual received power.

**KEYWORDS**: Programmed reflecting surface, passive components, OFDM, Intelligent Reflecting Surface (IRS), mean-square error, IEEE, Deep Learning, Convolutional Neural Network (CNN).

## I. INTRODUCTION

RIS stands for reconfigurable intelligent surface, a 2D surface of meta-materials whose properties can be changed rather of being fixed. It is an array of passive components that reflect the waves that are incident by changing its properties like scattering, absorption, reflection and diffraction. Utilizing software, all of these attributes are controllable. Each component of the IRS includes a configurable impedance that can be used to increase the signal's amplitude and phase-shift. IRS is a controllable part of the wireless propagation environment. It is neither a part of transmitter nor the receiver.

An IRS is a group of IRS units, each of which is capable of individually modifying the incident signal. The broad change could be in the frequency, phase, amplitude, or even polarization. An IRS uses no send power because most studies only take the incident signal's phase shift into account. An IRS essentially intelligently configures the wireless environment to help the communications between the sender and the recipient when direct communication has poor qualities.

Only one configuration can be submitted to the IRS at a time. Orthogonal Frequency Division Multiplexing (OFDM) systems are used as it prefers different configurations at a time. The channel estimation of both IRS configuration and OFDM systems combined can be used with heuristic algorithms. We take into account an OFDM system that has two imbalanced states per element, and we suggest a technique for channel estimation and setup. IRS placement examples include building surfaces, walls and ceilings.

**Problem Statement:**

A dataset includes transmitted and received signals that are reflected from a surface with 4096 elements that is intelligent and is said to have two separate states (+1 and -1). The signal impinging on the surface is reflected as a beam towards the receiver or scattered varying directions according to the configuration used for the IRS.

Each of the elements asserted to be capable of having two distinct states that produce 180-degree phase changes. By changing the pattern on the IRS and changing their phase shifts, the signal impinging on the surface should be reflected with different directivities like a beam in one direction. The goal is to predict the wireless channel at the receiver of a given IRS configuration.

As there are $2^{4096}$ configurations possible for the IRS, mathematical methods cannot be used to calculate the best configuration suitable for

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transmission. It was a big challenge for many researchers to estimate the best configuration suitable for transmission.

The Convolutional Neural Network is trained using the dataset provided and then it can estimate the channel by finding the signal power. The strongest and the weakest received signal power can also be found using the CNN. The estimated signal power explains about the channel of transmission.

**Aim of the project:**

In this project, CNN is trained with all the possible IRS configurations and then asked to predict the received signal for an unknown IRS configuration. This helps in estimating the wireless channel.

In wireless communication, OFDM is a modulation technique widely used for transmitting data over radio waves. It divides the available frequency spectrum into multiple orthogonal subcarriers, which are closely spaced and overlap in frequency. Each subcarrier carries a portion of the data, and the orthogonality ensures that they do not interfere with each other. This allows for efficient and robust transmission, especially in environments with multipath fading and interference.

In such cases, the received OFDM signal can be treated as an input to the CNN, where the convolutional layers can extract relevant features from the time-domain or frequency-domain representation of the signal. The subsequent layers of the CNN can then perform classification or regression tasks based on the learned features, identifying the modulation scheme or other signal characteristics.

**Intelligent Reflecting Surface (IRS):**

An intelligent reflecting surface contains meta-materials that can be set up to variously reflect wireless signals. And it can be utilized in wireless communications to improve the coverage. To make sure that the signal coming from the transmitter gets reflected towards the location of the receiver.

Suppose we put up a special surface that we call a reconfigurable intelligent surface (RIS) that captures all of the energy that makes through the window and then reflects it towards the user as a directive beam. These things are called reconfigurable because the properties of them can change with the position of the user. It is intelligent because it can be programmed to do something or can design algorithm to track the user and the surface is a two-dimensional thing.

Let us consider a transmitter sending out a wave to the surface. The surface takes the energy that reaches it and directed as a beam towards the user. There is a controller that can control the properties of the surface so that at another moment the signal can be directed towards another user.

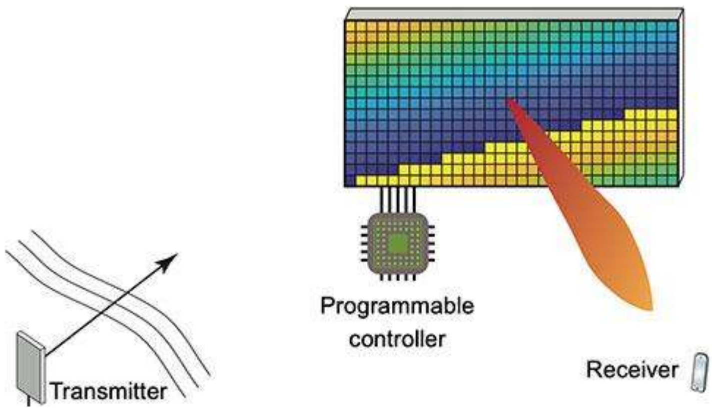


**Figure:** A typical use of IRS with a programmable controller

The colouring in the diagram demonstrates how the individual elements' filtering results in unique phase changes from $-\pi$ to $\pi$. The primary characteristic of the RIS is that the properties can be changed over time by external stimuli, which is why it is referred to be almost passive even if these elements are meant to do this filtering in a passive manner.

These behaviours can be controlled by dividing the surface into small pieces which can be called as a patch or meta-atom or an element. Every element is at the size smaller than the wavelength. This patch is connected to the controller via switch (diode) as shown in the figure that can change some properties like bias voltage or impedance. Changing the impedance will change the

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interaction of the element with the waves reaching it. It changes how the surface behaves. Whether it is a smooth or a rough surface or how the roughness or smoothness looks like in such way that we can control it to bounce in different directions.

In the basic configuration, the IRS has 1000 elements and each of the elements could only have two different states +90 and -90 degrees.

There are components with positive real part and negative real part. If the negative real part components are rotated by 180 degrees, they will be positive in the real part. We can't do anything about the imaginary parts but we can at least make sure that these parts add up relatively constructively. Spatial structure was used in the basic configuration. They put it up in the LOS path so we can only have strong path from the IRS to the transmitter and the RIS to the receiver. It is utilized to design a simple algorithm in which there was 17dB improvement using sparsity in the channel.

**Convolutional Neural Network:**

Three main types of layers make up the CNN: fully-connected (FC), pooling, and convolutional layers. When these layers are combined, a CNN architecture is produced. In addition to these three layers, two more important factors are the dropout layer and the activation function, which are described below.

**1. Convolutional Layer:**

This is the initial layer that is used to extract the various features from the input photographs. At this layer, a mathematical operation called convolution is performed between the input picture and a filter with the dimensions MxM. By moving the filter across the input image, the dot product between the filter and the areas of the image with respect to the filter size (MxM) is calculated. This gives information about the image, including its corners and edges, and is known as the feature map. Later, additional layers are given access to this feature map so they can learn new features from the input image.

**2. Pooling Layer:**

After a convolutional layer, a pooling layer is frequently applied. The primary objective of this layer is to reduce the size of the convolved feature map in order to reduce computing costs. Using fewer links between layers and independently modifying each feature map, this is accomplished. Depending on the technique used, there are many kinds of pooling procedures. It is essentially a summary of the features that a convolution layer produced. The feature map provides the largest contribution to Max Pooling.

**3. Fully Connected Layer:**

The Fully Connected (FC) layer, which also has weights and biases, is used to link the neurons between two layers. These layers are often positioned before the output layer and make up the last few layers of a CNN design. This flattens the input image from the layers beneath and provides it to the FC layer.

**4. Activation Functions:**

One of the most important components of the CNN model is the activation function. They are used to identify and approximate any kind of complex continuous link between network variables. It defines which model information should advance and which should not at the network's end, to put it simply. In turn, the network becomes nonlinear. Activation functions that are frequently utilized include the ReLU, Softmax, tanH, and Sigmoid functions. These operations each have a specific purpose.

## PROPOSED SOLUTION

**Dataset:**

The dataset provided concentrates on a single user. It contains 4N received signals through OFDM system which are obtained by transmission of known pilot signals over all subcarriers by using different IRS configurations. The variables provided in this dataset are given below

- K: Number of subcarriers = 500.
- M: Number of channel taps = 20.
- N: Number of IRS elements = 4096.
- pilotMatrix4N: It is a double matrix of size N x 4N = 4096 x 16384. Each column contains different configuration values -1 or +1 used during the transmission.
- receivedSignal4N: It is a complex double matrix of size K x 4N = 500 x 16384. While the pilot signal is transmitted using one of the setups in pilotMatrix4N, each column includes the signal that was received.
- transmitSignal: It is a double matrix of size K x 1 = 500 x 1. It is the pilot signal used for each transmission.

The dataset is given at https://github.com/emilbjornson/SP_Cup_2021

**IRS Configuration:**

Let us see an example of how the received signal is different over different subcarriers. We

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plot different configurations of receivedSignal4N given in the dataset to compare and identify the difference between them. As we can see in the figure below, four different configurations are plotted for the received signal 0, 1, 2 and 4096. The reason for plotting is that for configuration 0, all of the elements are set to +1 and the last one 4096th configuration, all the elements are set to -1. The magnitude of these received signals are divided by the symbol time 1/B, where B=10MHz bandwidth.

For each of the configurations, the received power in dBW over the subcarrier index are varying a lot due to channel fading behaviors. If we compare configuration 0 and configuration 4096, which have opposite values in their elements (+1 and -1), they look quite different. It means that they are interacting with the direct path in different ways.

We can say that taking 4N different configurations gives us more complexity to the system but gives more options to select better configuration between 4N = 16,384 different configurations.

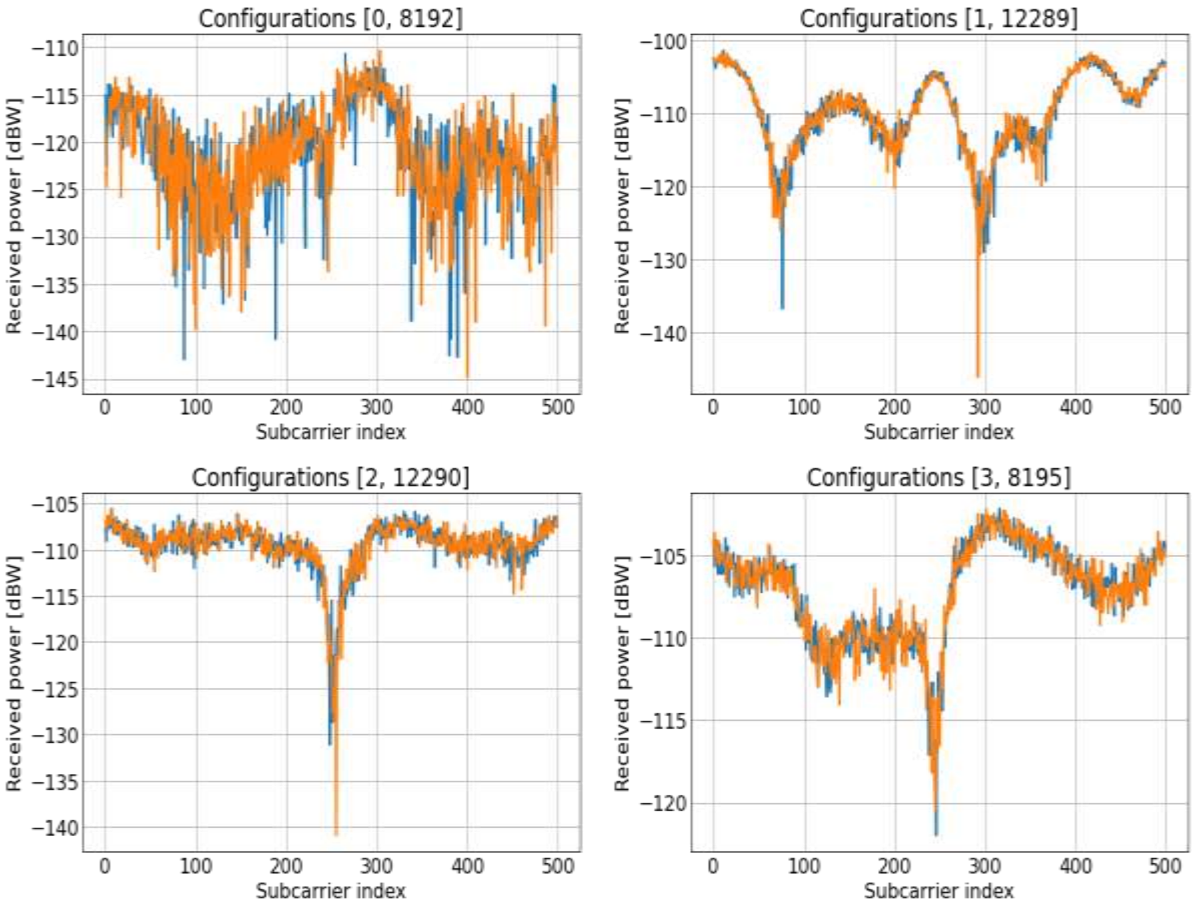


**Figure:** Plot of 4N received signal configurations of elements with similar values

The IRS configuration contains 4096 elements and again $2^{4096}$ different configurations. The strongest and weakest configurations can be plotted using MATLAB Simulation and the figure below shows the strongest received power in configuration 25 with almost -90dBW while the weakest received power found by plotting configuration 6172 with -122dBW of power. So, there is a power difference of almost 30dBW which is a lot. The other two random configurations are plotted of 7282 and 5721 configuration. The difference between strongest, weakest and random configuration signals can be observed in the figure below.

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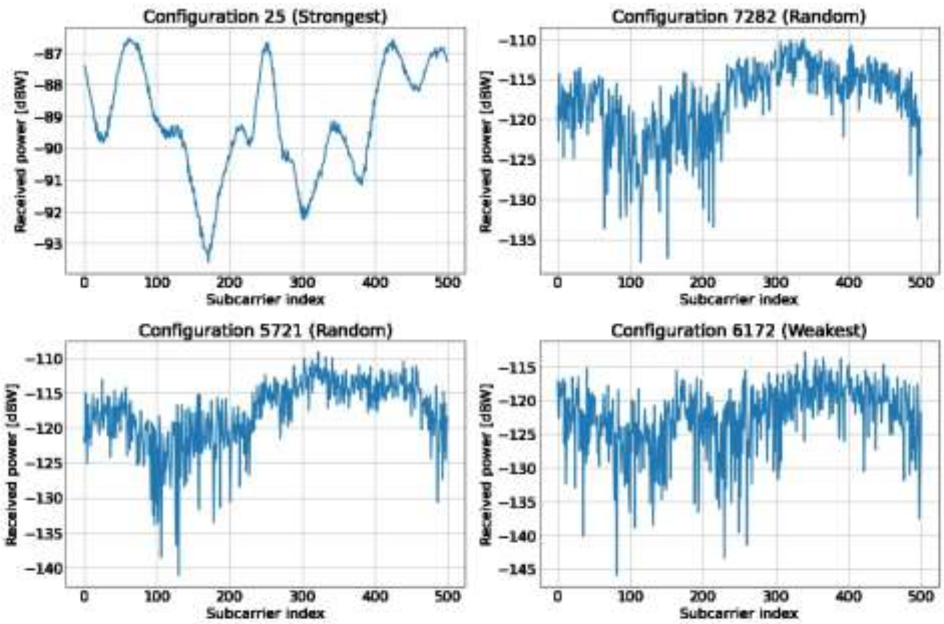


**Figure:** Strongest and weakest received power in dBW

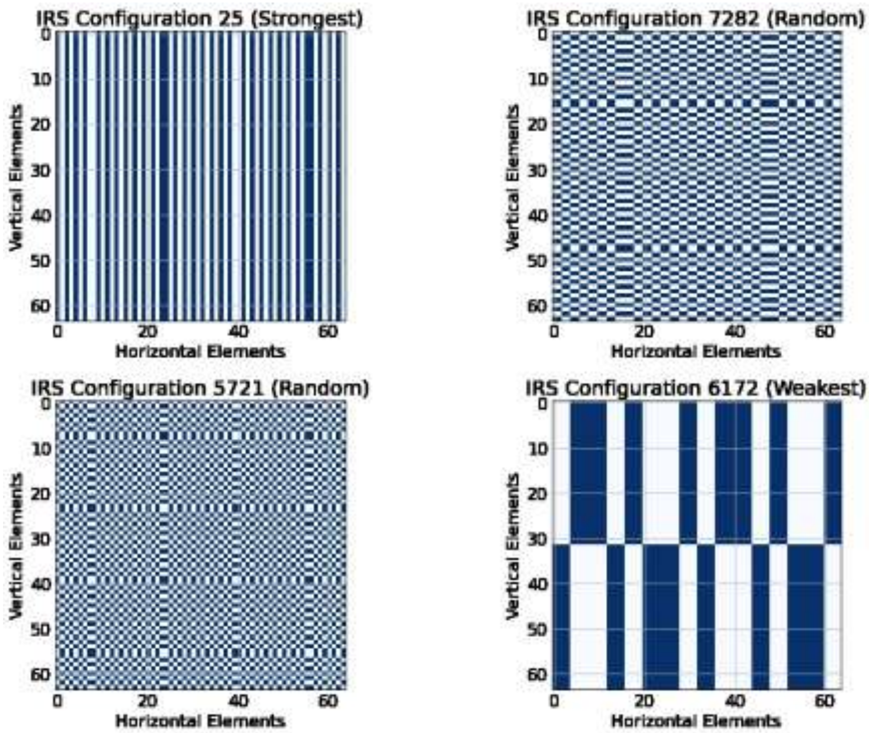


**Figure:** IRS Configurations of strongest and weakest received power (dBW)

The black and white parts in the configuration plots represent different values. Black parts represent -1 values and white parts represent +1 values. The best configuration is to be chosen from 4N different configurations for better received signal power and better data rates.

The configurations 25 (Strongest), 7282 (Random), 5721 (Random) and 6172 (Weakest) are compared and plotted using MATLAB Simulation. the graph is plotted with Subcarrier index on the X-axis and Signal power (dBW) on the Y-axis. As mentioned in the dataset, there are 500 subcarriers used for the IRS configuration. The strongest received signal have the average of -90 dBW while

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the other two random configuration signals and the weakest signal has the average value of approximately -120 dBW. The difference can be observed in a single figure which is shown below.

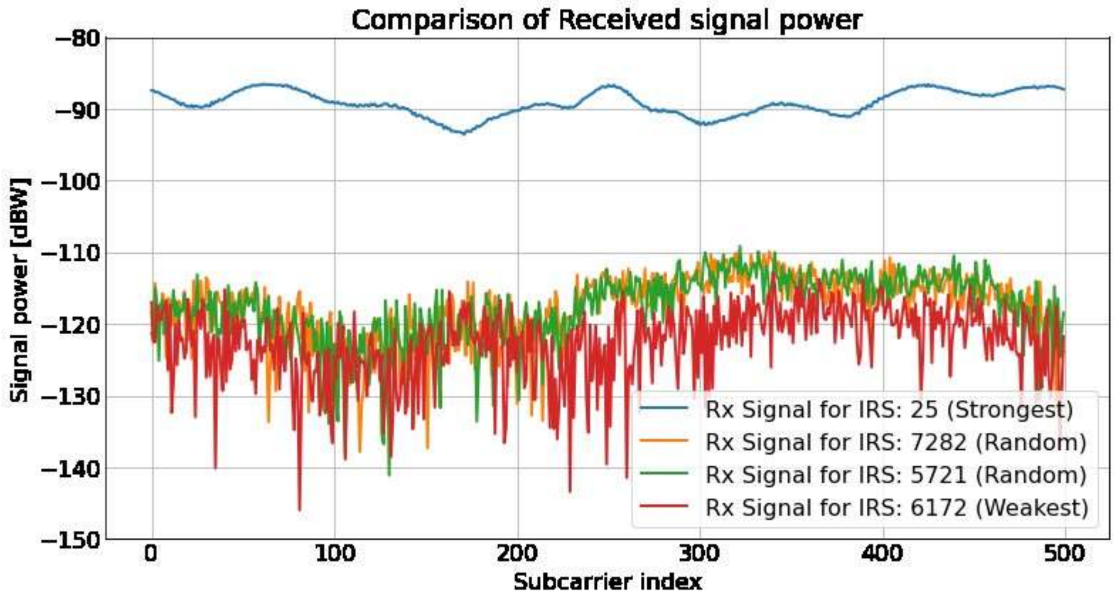


**Figure:** Comparison of strongest and weakest received power with random configurations.

When these strongest and weakest IRS configurations are retransmitted with a different configuration, there are slight fluctuations in the received power of the configurations rather than huge differences. The Orange and blue graph lines plotted between received power (dBW) and Subcarrier index is the received power of the first transmission and retransmission of the configurations of (25,12313) and (6172,14364) which are the strongest and weakest received power respectively.

**Proposed CNN:**

Convolutional neural networks (CNNs), a class of deep learning models frequently used for computer vision tasks like image classification, object identification, and image segmentation, contain a convolutional layer as a fundamental building component. The convolutional layer is in charge of applying convolutional operations to extract features from the input data.

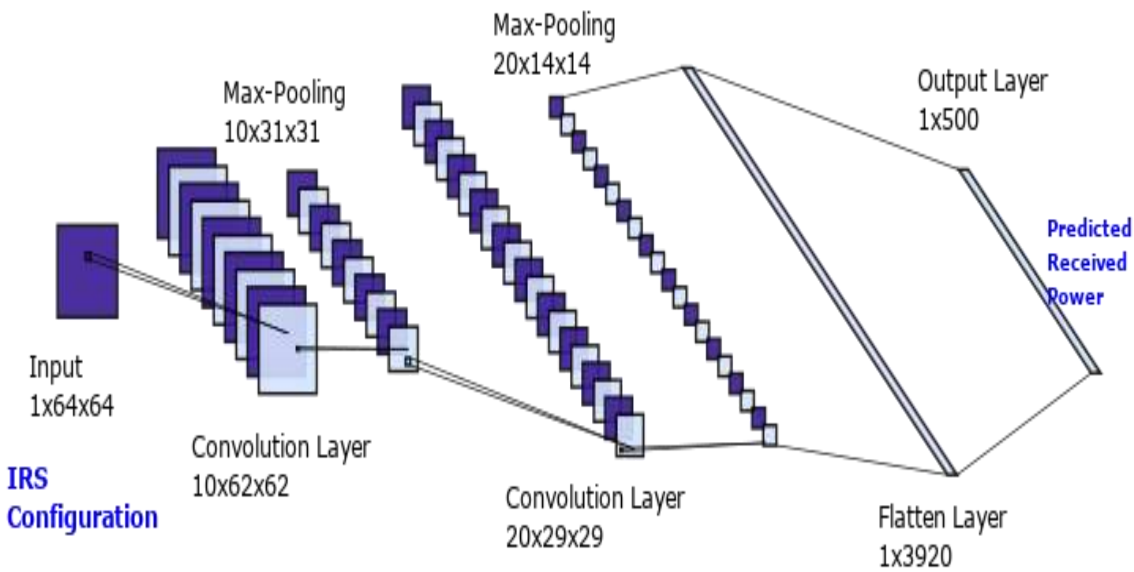


**Figure:** Convolutional neural network for IRS Configuration prediction.

An input of (1 x 64 x 64) dimension IRS configuration is used at the input side. Convolution operation is performed on the input resulting in (10 x 62 x 62) dimension configuration. It is passed through the max pooling layer which selects the maximum element from the region of the feature map covered by the filter. Thus, the output after max-pooling layer would be a feature map containing the most prominent features of the previous feature map. It results in (10 x 31 x 31) dimension feature map. The process is repeated again with convolution layer of (20 x 29 x 29) and max pooling layer of (20 x 14 x 14) dimension feature map.
The goal of layer flattening is to convert data into a 1-dimensional array that may be used by the following layer. The output of the convolutional layer was concatenated into a long feature vector. This layer connects to the final classification model and is entirely interconnected. Consider flattening a pooled feature map (20 x 14 x 14) into a single (1 x 3920) vector. Layer flattening converts multidimensional arrays into one-dimensional vectors as a consequence.
The output after performing all these operations is a (1 x 500) output layer which show
The dataset provided is used for training and validation purpose. 80% of the data is used for training the CNN as the training data should be more compared to the validation data. The remaining 20% of the data is used for testing or validation.
The graph is plotted between Epochs on X-axis and Loss function on Y-axis. The training and testing graph can be seen and compared in the graph.

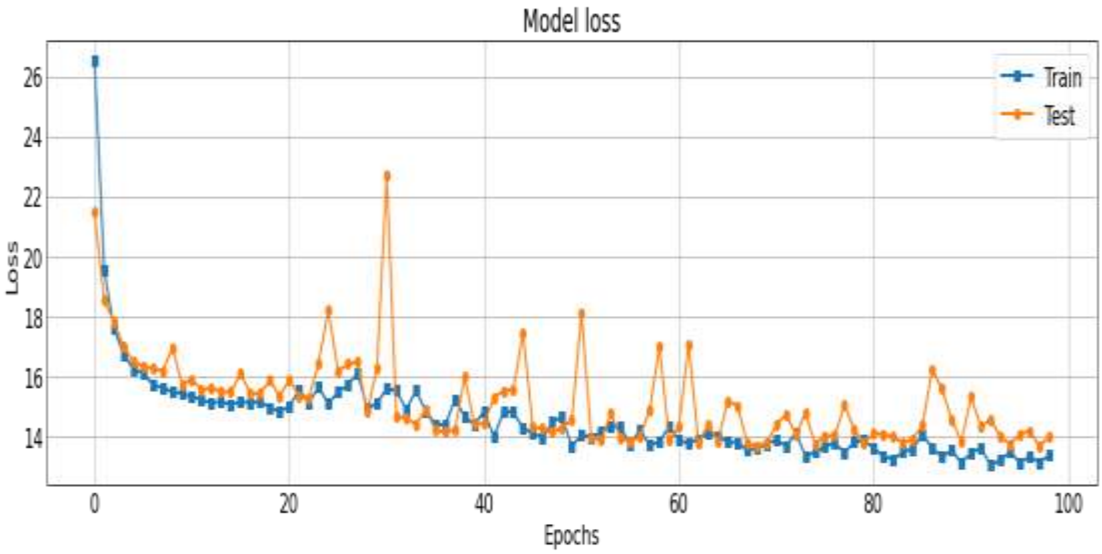


**Figure:** Training (80%) VS Testing (20%) Graph

**Hardware used:**
**Google Colab:**
Users can build, run, and collaborate on Python programs using the Google Colab (short for "Colaboratory") cloud-based platform. Due to its ability to offer free access to GPUs and TPUs.

## II. RESULTS OBTAINED

Here are some of the IRS configurations with actual and predicted received power with mean square error.

The received power graph is plotted between received power (dBW) and Subcarrier index on Y-axis and X-axis respectively. From the graph we can observe the predicted received power generated from the CNN model developed. It is almost similar the actual received power with a mean-square error of 11.46. The predicted signal is not a clean signal as it contains noise. But the average of both the signals is same.

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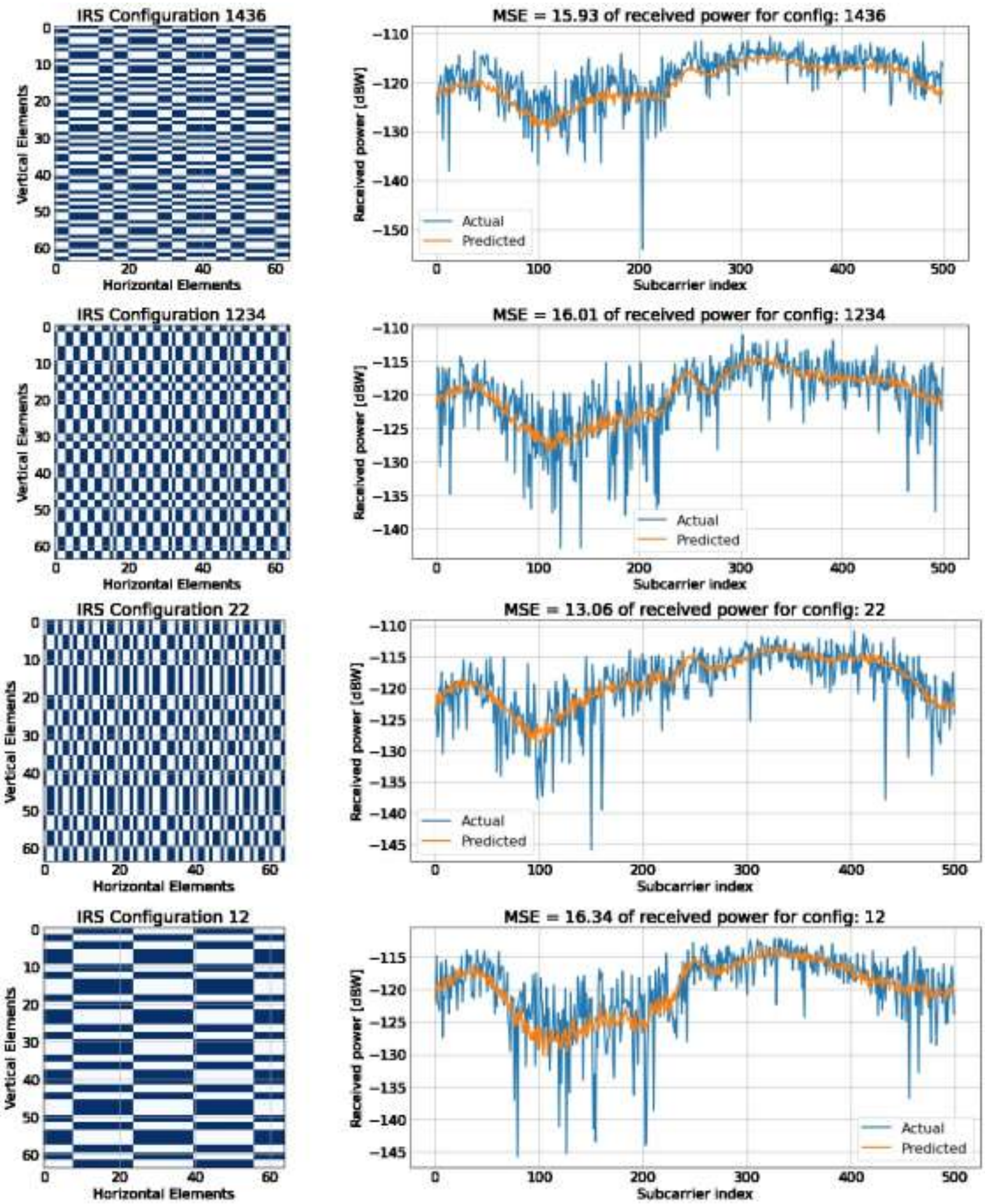


**Figure:** Actual and predicted received signals of IRS configurations.

The predicted received power plotted for the configurations of IRS (629, 586, 1436, 1234, 22 & 12) can be seen in the figures above and it can be compared with the actual received power. The mean-square error is also calculated and given. Any IRS configuration received power can be plotted using the Python software using in Google Colab.

## III. FUTURE SCOPE

The application of CNN (Convolutional Neural Networks) in IRS (Image Recognition Systems) seems extremely promising in the future. CNNs have completely changed the field of computer vision and image identification, and IRS has benefited greatly from their use. Following are some probable future opportunities and directions:

- **Enhanced Accuracy:** CNNs have previously shown remarkable performance in image recognition applications. However, ongoing studies aim to boost their reliability and precision even more.
- **Object Detection and Localization:** While CNNs are excellent at classifying images, there is ongoing study into how well they work at detecting and localizing objects. Future research may concentrate on integrating region-based algorithms.
- **Edge and Mobile Applications:** As edge computing and mobile devices become more common, there is a significant demand for lightweight CNN models that can perform IRS effectively on devices with limited resources.

These developments will open the door for more reliable and useful image recognition systems in a range of fields and sectors.

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