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A Survey on OFDM Channel Estimation using Artificial Intelligence

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Abstract*-Orthogonal Frequency Division Multiplexing (OFDM) can be considered as a key enabler in high speed and spectrally efficient communications. OFDM uses narrowly spaced sub-carriers for data transmission and is hence prone to errors in case the channel response changes for a particular frequency sub-band in the entire spectrum. It is therefore important to estimate the behavior of the channel for OFDM which is often termed as OFDM channel estimation. Due to the large data size and complexity of the data, it is often difficult to find patterns in the training data bits and hence channel estimation with high accuracy is difficult to attain. Off late, artificial intelligence (AI) is being used for the analysis of large and complex data patterns. In this paper, a survey is carried out on the use of artificial intelligence based approaches for OFDM channel estimation. The various approaches used with their respective pros and cons have been cited. Also, a system for effective and accurate OFDM channel estimation has been proposed. It is expected that the survey would render insight into the various approaches used for OFDM channel estimation and their relative merits and demerits.

***Keywords*: Artificial Neural Network (ANN), Deep Neural Network (DNN), ANFS- Adaptive Neuro-Fuzzy System, Orthogonal Frequency Division Multiplexing (OFDM), Channel Estimation.**

I. OFDM THEORY

Channel estimation for OFDM systems is particularly challenging due to the fact that the nature of wireless channels is completely random and do not follow any particular patterns. Hence OFDM channel estimation is a complex task. [1] Moreover, wireless cannel exhibit not only frequency selective behavior but also temporal variation. The training data hat is generally used for OFDM channel estimation is generally large and also exhibits complex and irregular patterns.

This makes the channel estimation difficult. Off late, artificial intelligence based techniques have been explored for OFDM channel estimation.[2] The spectrum of OFDM is depicted in figure 1.1. It can be seen that due to orthogonal sub-carriers, OFDM doesn't need guard band and hence considerable bandwidth is saved. A comparative analysis with frequency division multiplexing (FDM) has been shown. It can be clearly seen that OFDM saves a considerable amount of bandwidth thereby rendering much higher spectral efficiency.

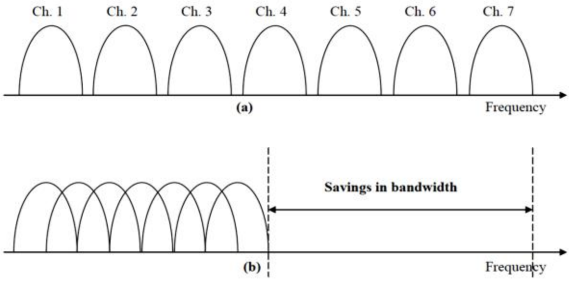

Fig. 1.1Comparatiev Specctra of FDM and OFDM

The next section focuses on the need for artificial intelligence for OFDM channel estimation and the basics of artificial neural networks.

II. NEED FOR DEEP NEURAL NETWORKS FOR OFDM CHANNEL ESTIMATION

As mentioned earlier, wireless channels are highly random in nature and estimating their channel response with high accuracy is a difficult task. [3]The OFDM channel is just not a function of frequency but also a function of time. Mathematically, the time and frequency dependent channel response of a wireless channel is given by:

$$H = g(f, t) \qquad (1)$$

Here,

g is a function of

f represents frequency

t represents time

H represents channel response

The graphical illustration of such a time-frequency dependent channel response is given by:

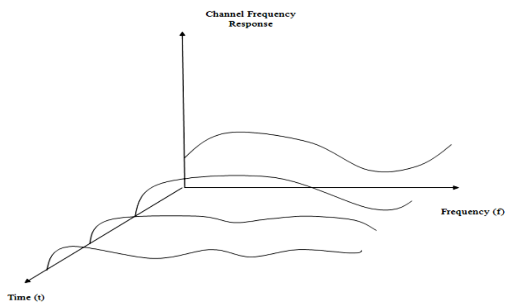

Fig. 2.1Grahical illstration of channel frequency response of a random wireless channel

The channel is genrally estimated by sending a dummy data (X) through the channel. [4]When the data is received by the receiving end, termed by (Y), the values of X and Y are compared to estimate the condition of the channel. However, Y would be a function of time since the channel characteristics are a funtion of time i.e.

$$Y = f(t) \text{.......................................(2)}$$

Here,

X is the transmitted bit stream

Y is the received bit stream

t is time

Hence the channel needs to be sensed at regular intervals called T_P where T_P is the time after which the chhanel needs to be sensed in order to find its characteristics. The time period for channel estimation should be less than the time in which the chanel changes its characteristics i.e.

$$T_P < \tilde{T} \text{...(3)}$$

Here,

$\tilde{T}$ is the time in which the channel changes.

The channel thus needs to be sensed regularly in order to update the channel state information.

III. INTRODUCTION TO DEEP NEURAL NETWORKS AND DEEP LERNING

Deep neural networks are a category of neural networks which have multiple hidden layers. The graphical representation of deep neural networks is shown in the figure below:

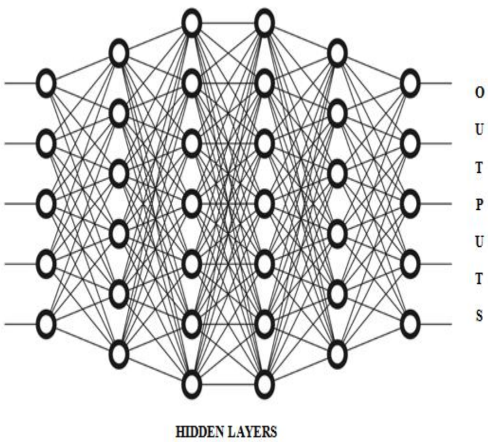

Fig. 2.1Grahical represnetation of Deep Neural Network (DNN)

Deep neural networks have multiple hodden layers. Generally any neural network has three layes viz. input layer for accepting data, hidden layer for analyzing data and output layer for producing the output. [2] The mathematcial formulation for the output of a neural network is given by:

$$y = \sum_{i=1}^{n} x_i w_i + \theta \text{...................................(4)}$$

Here,

y is the output of the neural network

x is the parallel input to the neural network

w is the weight

$\boldsymbol{\theta}$ is the bias

n is the number of parallel data streams.

Generally, deep neural networks are used for applications with highly complex data patterns. There are several variants of neural networks which are being explored for the analysis of highly complex data patterns such as neuro fuzzy systems which can be considered to be a combination of neural networks and fuzzy logic. It has been seen that more complex data patterns may need probabilistic or fuzzy appraoches for a more accurate estmation. Typically, neural networks are trained with 70% of the data and tested with 30% of the data to evaluate the accuracy.

IV. PREVIOUS WORK

In this section, the major contribution of significant work in the domain is cited.

In 2018, C Hager et al. in [2] proposed a technique to estimate the characteristic of non-linear interference (NLI) in optical networks. The proposed approach used differential learning rule based on deep neural network for the estimation of the characteristics of the optical fibers for long haul networks. It was shown that deep neural networks were effective in the data analysis of optical systems showing temporal variation as compared to conventional techniques for estimation.

In 2017, H Ye et al. in [3] proposed an approach using deep learning for OFDM channel estimation and signal detection. The approach used a model with variable number of pilots for the estimation of the channel frequency response. The variation of the number of pilot bits was shown to affect the bit error rate of the system. The increased number of pilots had a positive effect in reduction in the bit error rate. The other metrics for the evaluation of the system were the mean square error, the number of iterations and the time of execution.

In the year 2017, C Jiang et al. in [4] proposed a technique using machine learning for the channel estimation of next generation wireless networks. The proposed system targeted the 5G networks for enhanced data transfer schemes. The future generation communication systems would rely heavily on channel estimation of wireless networks. The estimation of wireless channels is done using machine learning algorithms such as neuro-fuzzy expert systems, genetic algorithms and optimization techniques. It is shown that the machine learning based approaches are effective enough in high accuracy predictions.

In the year 2016, Eliya Nachmani et al. in [5] proposed deep learning for the sake of decoding of codes. It used the concept of deep belief networks. It was an approach using a concatenated approach using the parallel decoding of codes using deep learning. Deep neural networks were used for the fabrication of the decoding structure with the training of the decoder acting as the apriori probability for the decoding of the code bits. The error propagation in the decoding tree is evaluated in terms of the nit error rate. The complexity of algorithm is done in terms of the number of iterations.

In the year 2016, X Wang et al. in [6] proposed a technique using deep neural network for estimating channel state information (CSI). The approach is called Deep-Fi. The channel state information (CSI) is critical in the design of a receiver structure using an equalizer. The channel state information is used in this system to design an equalization mechanism that would eventually reverse the effects of the channel.

V. PROPOSED ALGORITHM

In view of the different approaches studied so far, an optimized approach for channel estimation has been proposed:

1. Data in terms of binary bits from multiple usrs can be generated as:

$$\boldsymbol{X}_{Serial} = (rand(1,n) \dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (5)$$

Here,

X_{Serial} represents the serial data.

Rand(1,n) exhibits a serial data stream of n-bits.

It is necessary to generate data bits which are random since user data is always reandom in nature.

2. Sub carriers can be genrated using the IFFT operation which are both orthogonal and narrowly spaced. Local oscillators can be replaced by the IFFT block:

$$X_{IFFT} = ifft(X_{Serial}) \dots\dots\dots\dots\dots\dots (6)$$

Here,

X_{IFFT} is the modulated version of the random data bits generated above.

3. Addition of Pilots.

The use of pilot bits are used for synchroniation purposes and add overhead to the data stream.

$$X_{Pilot} = X_{end} - N \quad (7)$$

Here,

X_{Pilot} reppresentsthe number of pilot bits.

X_{end} represents the ending bit of the data stream

N persents the appended bit size.

4. The received signal at the receiving end of the channel is given by:

$$Y_{OUT} = f(X_{IN} \dots\dots\dots\dots\dots\dots (8)$$

Here,

f represents the channel function governing the input output channel mapping.

X_{IN} represents the input data stream of the channel and is given by;

$$X_{IN} = X_{IFFT} + X_{PILOT} \dots\dots\dots\dots\dots\dots (9)$$

Any practical channel is a characterized by the addition of noise in the channel. The noise considered in this case is gaussain noise with a constant power spectral density (psd) for all frequencies.

5. Afetr the addition of noise, the output of the channel is the following noise added signal.

$$Y_{OUT} = X_{IN} + Noise_{Channel} \dots\dots\dots\dots\dots\dots (10)$$

Here,

Y_{OUT} represents the output of the channel before noise addition

X_{IN} represents the input signal to the channel

$Noise_{Channel}$ represnets the noise effects which get intertwined to the signal while passing through the channel.

6. The subsequent step is the design of a neural network with multiple hidden layers often called a deep neural network. The training algorithm that is proposed to be used is the Bayesian regularization (BR) training algorithm. The weight updating rule for the BR algorithm is given by:

$$w_{k+1} = w_k - (J_k J_k^T + \mu I)^\wedge - 1(J_k^T e_k) \quad \dots\dots\dots (11)$$

Here,

w_{k+1} is weight of next iteration,

w_k is weight of present iteration

J_k is the Jacobian Matrix

J_k^T is Transpose of Jacobian Matrix

e_k is error of Present Iteration

μ is step size

I is an identity matrix.

The BR algorithm also taken ito account the Baye's theorem of conditional probaility mathematically stated as:

$$P\frac{A}{B} = \frac{P(A).P\frac{B}{A}}{P(B)} \quad (12)$$

Here,

$P\frac{A}{B}$ is the probability of occurrence of A given B is true.

$P\frac{B}{A}$ is the probability of occurrence of B givenA is true.

$P(B)$ is the probability of occurrence of B

$P(A)$ is the probability of occurrence of A

In the training process, the general rule of the thumb is that 70% of the data is fed to the neural network for training and 30% of the data is fed to the neural network for testing.

VI. EVALUATION PARAMETERS

The evaluation parameters for the evaluation of the proposed approach are:

1) Mean Square Error

2) Number of iterations needed for training

3) Bit Error rate

The mean square error is mathematically defined as:

$$mse = \frac{1}{n}\sum_{i=1}^{n}(y_p - y_a)^2 \quad (13)$$

Here,

mse stands for mean square error

n is the number of predicted samples

y_p is the predicted output

y_a is the actual output

Bit error rate (BER) is mathematically defined as:

$$BER = \frac{Number\ of\ error\ bits}{Total\ number\ of\ bits\ transmitted} \quad (14)$$

VII. CONCLUSION

From the previous discussions, it can be concluded that OFDM channel estimation is complex since the wireless channels exhibit random nature and has temporal variation. The channel is therefore needed to be sensed so as to update the channel state information (CSI). The channel state information keeps changing with time and hence the channel needs to be sensed periodically before the channel characteristics change. The paper presents a deep neural network approach for OFDM channel estimation. The significant approaches in the field have been cited with the pros and cons. A proposed system model using the Bayesian Regularization training rule has also been proposed. It is expected that this survey will pave the path for effective system design.

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