

# Training Based Channel Estimation and DL Estimation in OFDM System

<sup>1</sup>Shivani Bamotra, <sup>2</sup>Baldev Raj, <sup>3</sup>Sameru Sharma

<sup>1</sup>Student, <sup>2</sup>Associate Professor, <sup>3</sup>Principal

<sup>1</sup>Department of Electronics and Communications

<sup>1</sup>Government College of Engineering and Technology, Jammu, J&K, India

**Abstract:** For Wireless communication, Channel estimation is a backbreaking issue to retrieve original data. Without needing any previous learning of channel statistics, every signal model is allowed by DL based channel estimation and it is accessed to the (MMSE) minimum mean-squared error estimation in numerous schemes. The several channel estimation methods and OFDM system is described in this paper. (Abstract)

**Index Terms:** Channel Estimation, OFDM (key words)

## I. INTRODUCTION

### A. Review of OFDM

OFDM is the advanced form of FDM that may be utilized as a automated multi-carrier modulation strategy. The carriers are splitted into sub-carriers in which OFDM's orthogonality is occurred.[1]. Every sub-carrier is modulated by QPSK or QAM modulation techniques. In OFDM, the huge data streams is partitioned into parallel data streams for transmission. High data rates and frequency selective channels are modified by precise form of multi-carrier transmission :- OFDM. Hence, the OFDM discovers it's applications in mainly recent broadcasting wireless systems particularly , WiMax, DVB>LTE, (UWB) Ultra Wide Band systems and (WIFI) 802.11n.

### B. Merits

Guard bands are not needed as sub-channel's distortion is avoided by OFDM's orthogonality.

The high spectral efficiency is attained by the orthogonality of OFDM.

Between the receiver and the transmitter, OFDM demands valid frequency synchronization.[1]

### C. Representation

Transmitted input symbols:-  $X_k$ ,  $k=0,1, \dots, N-1$

Frequency spacing :-  $f_s$  (for orthogonality)

where  $f_s = 1 / NT_s$

$T_s$ -> Sampling Interval

Transmitted signal =  $X_n = X_k e^{j(2\pi f_s k n)}$

Data symbols=  $X_k$

Sub-carriers=  $N$

OFDM time symbol =  $T$

## II. CHANNEL ESTIMATION

The data symbol of OFDM is retrieved by processing signal method. The channel estimation is the phase shift estimate for each subcarrier . The numerous techniques of channel estimation are:-

1) Frequency domain Pilot Assisted Approach

2) Time domain assisted approach

Receiver's constellation is de-rotated by channel estimation.

### Categorization of Channel Estimation Strategies :-

Channel estimation is categorized as semi-blind; training based and blind channel's estimation. Here, training based estimation is focused. Figure 1 shows training based algorithms.

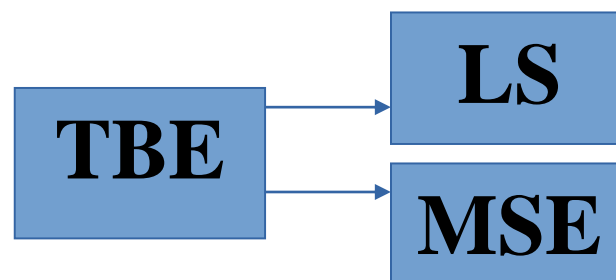


Fig. 1 Training based estimation algorithm

**Training Based Channel Estimation Techniques:-**

[1]-[5],[7] and [10] have presented many channel estimation and optimization techniques.

To appraise the channel, the training pilots or the symbols are utilized. To minimize other's faults, (MMSE) Minimum Mean Square Error algorithms and (LS) Least Square estimate are used. Training symbol based channel estimate is best than others.

1) (LS) Least Squared Estimation :-

To minimize squared error, LS method is utilized without channel statistics preceding knowledge in between the original data and the received data. It can diminish the MSE and BER like errors. The pilot sub carriers is considered, its channel estimate is

$$\hat{X}_p = Y_p / \hat{H}_{pLS}, \text{ where } \hat{H}_{pLS} = F(Y_p / X_p) \tag{1}$$

where estimated signal =  $\hat{X}$ , interpolation operator =  $F(\cdot)$ , LS channel estimates is contained by  $\hat{H}_{LS}$ , transmitted and received pilots:-  $X_p$  and  $Y_p$ .

2) Least Minimum Mean Square Error :-

The Mean Square Error is diminished by using LMMSE channel estimation scheme. The channel's 2nd order statistics is oppressed in it. However, LS estimate is less complicated than LMMSE evaluation.  $\hat{H}_{pLMMSE}$  is the depiction of LMMSE channel estimate and it is

$$\hat{H}_{pLMMSE} = R_{HHp} [R_{HpHp} + (\beta/\alpha)I_p]^{-1} \hat{H}_{pLS} \tag{2}$$

where certain modulation scheme constant =  $\beta$ , channel realization co-variance matrix;  $H$  in frequency-domain:-  $R_{HHp} = E\{H^* \cdot i H H^* \cdot i\}$ , SNR in linear-domain =  $\alpha$ .

**LS Vs LMMSE Vs DL Estimator :-**

LS ESTIMATOR	LMMSE ESTIMATOR	DL ESTIMATOR
MSE = JLS High MSE	MSE= JLMMSE	MSE=J(f0)
Linear models	Linear models	Linear models & Non-linear models
Low accuracy	Accurate	More accuracy and efficiency
Very low complexity	High computational complexity	Complex and rate of convergence is faster than LS and LMMSE
Non-linear model's estimate performances is degraded.	Channel co-variance matrix precision determines it. Better perform than LS. Degrades for non-linear model	It has dynamic learning capacity and superb generalization potential in interference and defective corrupted systems. It has simplicity and stability of linear estimators. More flexible and general collated to LMMSE and LS.
$LS_{\text{performance}} = 1 / SNR$	$JLMMSE \leq JLS$	BER decreases with increase in SNR For Linear systems, $JLMMSE = J(f0) \leq JLS$

**III. DCCN CHANNEL EQUALIZER:-**

Input  $y_{cp}$  to equalizer. It contains 4 submodules.

- 1) It contains thick layer,  $C_{S \times N}$  which is followed by  $N \times N \times 1, C$ -Conv layer. It converts  $y_{cp}$  to  $Y$ .
- 2) It consists of 2D complex filter and four dense layers which estimates channel frequency response ' $\hat{H}$ '.
- 3) Element-wise complex division and equalization is occurred in it,  $\hat{H} = \hat{X}/Y$ . IDFT converts  $\hat{X}$  to  $\hat{x}$ .

$$\hat{x} + C_{p \text{ dense layer}} \rightarrow \hat{x}_{cp}$$

4) To locate and estimate  $\hat{H}_{pLS}$ ; channel co-efficients on pilots,  $C_{FN \times P}$  is depicted. Like LRA-LMMSE [7], 2D filter and three dense layers performs channel estimation.

$$\hat{H}_{LRA} = U D_p U^H \hat{H}_{LS} \tag{3}$$

where unitary matrix:-  $U$ , diagonal matrix:-  $D_p$ .

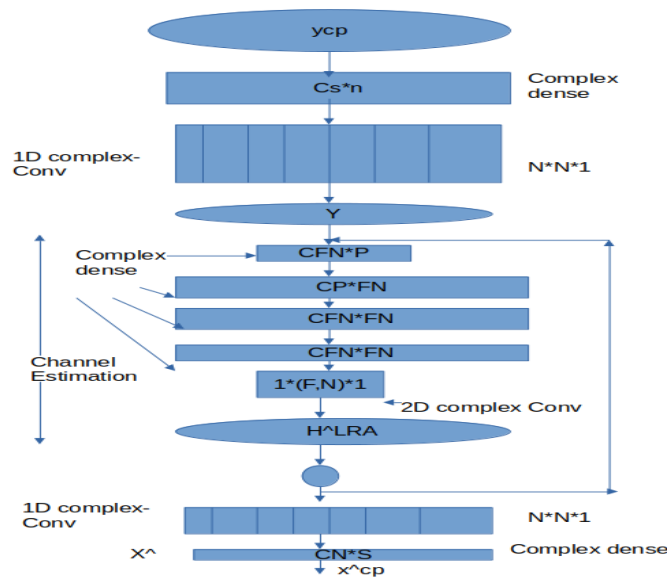


Fig.2 DCCN Equalizer

**IV. DCCN BASED CHANNEL ESTIMATION :-**

Input is received data and output is transmitted data in DCCN that is trained offline. The narrowband Rayleigh fading channel model is utilized. In OFDM, generating the training data for a user. There is random generation of transmitted symbols and pilot in frame of OFDM. By two different optimization algorithms, error is minimized between the trained output and the original transmitted data in DNN model. The analysis of estimator performance is done by these optimizers. The two optimizers are adaptive (Adam)moment estimation ; (SGDm)stochastic gradient descent with momentum.

A) Stochastic gradient (SGD) descent:- For neural networks faster convergence,this is used. To perform every iteration, some samples from the complete dataset is exploited. SGD is statistically affordable inspite of requiring extra iterations to arrive at the global minimal than gradient descent [5], [6]. For improving the convergence speed, SGD (SGDm) with momentum is applied. In SGDm, the network parameters are updated by computing gradient moving average. The  $(\theta)$  network parameters and (s) moment vector at 't' iteration are [5], [6]:

$$(\theta_{t-1}) = \theta_t + \alpha s \tag{4}$$

$$s_t = (\beta * s_{t-1}) + (1-\beta) * \text{grad}(\theta_{t-1}) \tag{5}$$

B) (Adam) Adaptive moment estimation:- Algorithm becomes special by combining the advantages of momentum and RMSprop. Adaptive learning rates is employed to upgrade the network parameters thus it has rapid optimization. To train DNN,it is recommended. By using Adam optimizer, the web parameters are [5], [6]:

$$s_t = (s_{t-1} * \beta) + \text{grad}(\theta_{t-1}) * (1-\beta) \tag{6}$$

$$u_t = \text{grad}(\theta_{t-1})^2 * (1-\beta) + \beta u_{t-1} \tag{7}$$

$$(1-\beta^2) = u_t / \hat{u}_t \tag{8}$$

$$\alpha(\hat{s}_t / \sqrt{\hat{u}_t + \epsilon}) = (\theta_{t-1}) - \theta_t \tag{9}$$

$$(1-\beta^1) = s_t / \hat{s}_t \tag{10}$$

**V. CONCLUSION**

The study of (OFDM) orthogonal frequency division multiplexing system is reviewed. Out of the several channel estimation techniques, the training symbol based channel estimation techniques such as LS, LMMSE are studied. DL estimator is better than the other two. The DCCN based channel estimation with optimizers (SGD abd Adam) and the DCCN based Equalizer are discussed. Each optimizer has useful characteristics. Adam computation is complex than SGD but more useful to train DNN.

**VI. ACKNOWLEDGEMENT**

The writing about “Training Based Channel Estimation and DL Estimation in OFDM System” under supervision of Mrs Sameru Sharma and Mr Baldev Raj is a big chance for me and I acknowledge with credit to them.

**REFERENCES**

1. Zhou, Wen, and Wong Hing Lam. "A fast LMMSE channel estimation method for OFDM systems." EURASIP Journal on Wireless Communications and Networking 2009 (2009): 1-13.
2. Hung, Kun-Chien, and David W. Lin. "Pilot-based LMMSE channel estimation for OFDM systems with power–delay profile approximation." IEEE Transactions on Vehicular Technology 59, no. 1 (2009): 150-159.

3. Savaux, Vincent, Faouzi Bader, and Yves Louët. "A joint MMSE channel and noise variance estimation for OFDM/OQAM modulation." *IEEE Transactions on Communications* 63, no. 11 (2015): 4254-4266.
4. Ye, Hao, Geoffrey Ye Li, and Biing-Hwang Juang. "Power of deep learning for channel estimation and signal detection in OFDM systems." *IEEE Wireless Communications Letters* 7, no. 1 (2017): 114-117.
5. Govil, Rakshit. "Different types of channel estimation techniques used in MIMO-OFDM for effective communication systems." *Int J Eng Res Technol (IJERT)* 7, no. 07 (2018): 271-275.
6. Qiang, Hu, Gao Feifei, Zhang Hao, Jin Shi, and Li Geoffrey Ye. "Deep learning for MIMO channel estimation: Interpretation, performance, and comparison." *arXiv preprint arXiv:1911.01918* (2019).
7. Zhang, Jiawei. "Gradient descent based optimization algorithms for deep learning models training." *arXiv preprint arXiv:1903.03614* (2019).
8. Chauhan, Rishika, Shefali Sharma, and Rahul Pachauri. "Deep Neural Network-based Channel Estimation In OFDM Systems."
9. Soydaner, Derya. "A comparison of optimization algorithms for deep learning." *International Journal of Pattern Recognition and Artificial Intelligence* 34, no. 13 (2020): 2052013.