iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: VI Month of publication: June 2023

DOI: https://doi.org/10.22214/ijraset.2023.54202

Deep Learning Aided 5G Channel Estimation

Dr. M. Vijaya Lakshmi[1], B. Shashitha[2], B. Alekhya[3], Clementina Rithika[4], CH. Bhavana[5]
[1]Assistant Prof ETE, GNITS, Hyderabad, India
[2, 3, 4, 5]B.Tech, GNITS, ETE Department, Hyderabad, India

Abstract: Wireless communications involves the transfer of voiceand data without a cable or wires. It uses orthogonal frequency-division multiplexing, also known as a multicarrier transmission technique. In multiple input multiple output (MIMO) wireless communication (4G and5G technologies), channel estimation is crucial. Multiple antennas are used at both the transmit and receive sides ofa MIMO system to increase spectral efficiency and reliability.

In 5G channel estimation is performed to improve the accuracy of the received signal. Least-squares estimation is a cheap method with relatively large channel estimationerrors, but it is supported in this work by using a new channel estimation method that leverages deep learning. LS (least squares) and MMSE (minimum mean squared error) are two popular traditional approaches to channel estimation, but deep learning provides much more accurate results than previous channel estimation methods.

Keywords: OFDM, LS, MMSE, DL

I. INTRODUCTION

Fifth generation (5G) wireless technology was developed to accommodate the exponential increase in wireless data traffic and communication reliability. To overcome frequency selective fading in multipath propagation environments, OFDM (Orthogonal Frequency Division Multiplexing) technology is a naturalsuccess in existing networks. As a result, this method improves spectral efficiency compared to single-carrier approaches. Pilot symbols known to the transmitter and receiver are typically used for channel estimation.Depending on different deployment scenarios, 5G systempilot symbols can have different structures. Least-squares(LS) estimation is one of the traditional techniques for channel estimation with minimal computational effort, asit does not require prior knowledge of the statistical channel information.

However, in the context of many applications, this estimation method gives relatively poor results. As an alternative, a minimum mean squared error (MMSE) estimation approach was developed to reduce the average channel estimation error. However, the MMSE estimationapproach is significantly more computationally complex as it requires channel statistical data, especially the mean and covariance matrices. DNN (deep neural network)models with two different architectures are used for frequency selective fading channel estimation in 5G MIMO OFDM systems. The effectiveness of the proposed deep learning-assisted channel estimation is then evaluated using two different receiver velocity-based scenarios. The performance of DNN-based channel estimation is compared with that of conventional LS and linear MMSE (LMMSE) in terms of mean squared error (MSE) and bit error rate (BER) versus signal-to-noise ratio (SNR) criteria. Estimate.

II. METHODOLOGY

Adaptive systems, called neural networks, also known as artificial neural networks, learn using nodes, or neurons, interconnected in a layered structure similar to the human brain.Neural networks can be trained to recognize patterns, classify data, and predict future events by learning from data. Neural networks abstract their inputs in layers. Similar to how the human brain recognizes patterns in sounds and images, it can be trained using different instances. Its behavior is determined by the connections between components and the weight or strength of these connections.

As long as there is no inter-carrier interference, each sub-carrieris represented as an independent channel and orthogonality between sub-carriers is maintained. Orthogonality allows each subcarrier component of the signal to be represented as the Hadamard product of the channel frequency response at the transmitted signal and the subcarrier as

$$y_b(t) = \sum_{a=1}^{NT} h_{a,b}(t) \odot X_a(t) + n_b(t)$$

where n_b (t), $h_{a,b}$ (t) ,and x_a(t) are the noise, channel, and Fourier transforms of the signal, except when working in the frequency domain.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VI Jun 2023- Available at www.ijraset.com

Block Diagram

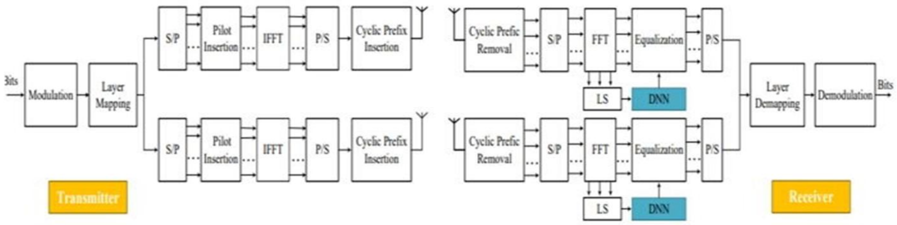

Fig 1.1: DNN structure used for channel estimation

A. *DNN-Aided Channel Estimation*

To overcome the aforementioned problems of LS and LMMSE estimation, DNN-based estimation is proposed toreduce the MSE between the channel estimate derived by LS estimation and the actual channel. The figure shows the structure of the proposed DNN-based estimation.

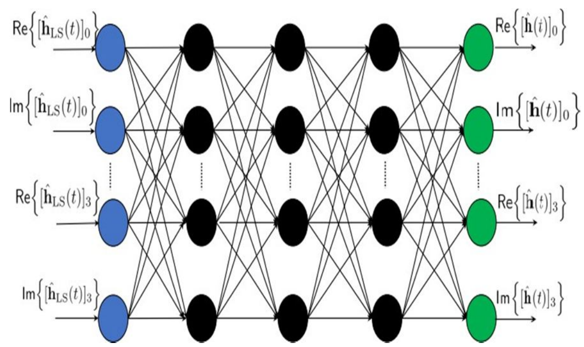

Fig 5.2: DNN structure for channel estimation

The organizational structure of the proposed DNN structure includes input layer, hidden layer and output layer. DNN may have a secret level tone. However, the proposed DNN structure for the MIMO-OFDM system under consideration consists of three hidden layers, each containing many neurons. Specifically, a neuron, which isa type of arithmetic unit, performs the following calculations

$$o = f(z) = f(\sum_{i=1}^{M} w_i x_i + b)$$

where M indicates number of inputs to the neuron forwhich x_i is the i-th input (i = 1, . . . , M);
w_i is the i-th weight corresponding to the i-th input; o isthe output of the neuron and b represents the bias.
f(.) is called as an activation function
which is used to classify the nonlinearity of the data.

To minimize MSE, DNN-based estimation learns realchannel information using the channel estimate obtained by LS estimation as input, and defines the realization of the input to the training process as:

$$I_{nt} = \{Re\{[\hat{h}_{LS}(t)]_0\}, Im\{[\hat{h}_{LS}(t)]_0\}, \ldots, \{Re\{[\hat{h}_{LS}(t)]_3\}, \{Im\{[\hat{h}_{LS}(t)]_3\}$$

where the real and imaginary parts of the complex numberare given by Re and Im, respectively, and the superscript n denotes the nth realization. Here is the output of the neural network:

$$O_{nt} = \{Re\{[\hat{h}(t)]_0\}, Im\{[\hat{h}(t)]_0\}, \ldots, Re\{[\hat{h}(t)_3\}, \{Im\{[\hat{h}(t)]_3\}$$

Where $\hat{h}(t)$ represents the output of the neural network at realization n. To handle complex numbers in neural networks, the above equation divides thechannel estimate into real and imaginary domains. Assignments are handled individually by the learning process.

The original transmitted data and received signal are recorded as training data. The data received from the data block and pilot block are the inputs to the deep learning model. The model is trained to reduce discrepancies between the submitted data and the neural network output. There arevarious ways to show the difference.

$$L = \frac{1}{N}\sum_{k}(\hat{X}(k) - X(k))^2$$

where L is the loss, X(k) is the monitoring message for this scenario, $\hat{X}(k)$ is the prediction, and X(k) is the set of transmitted symbols. A DNN model consists of three layers,one of which is the hidden layer. Each layer has 16, 10, and4 neurons, respectively. The input numbers correspond to thesum of the real and imaginary sections of the two OFDM blocks containing transmitted symbols and pilots. Group andpredict all 16 bits of the transmitted data using a single, independently trained model. The predictions are then addedto produce the output.

Dataset is divided in to 3 sample sets.\

- Training: These are presented to the network duringtraining and adjusted according to errors.
- Tests do not affect network performance, so they are areliable indicator of network performance during and after training.
- Validation: Used to assess how well the network is generalizing and stop training if it stops improving.

There are several ways to split the data, but the default method allocates 70% of the data for training, 15% forvalidation, and 15% for testing.

III. RESULTS AND DISCUSSIONS

A. *BER VS SNR for Deep Learning Channel Estimation*

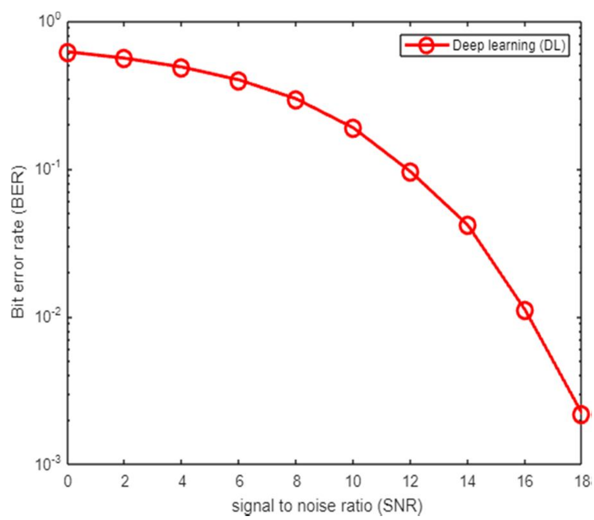

Fig 3.2 BER VS SNR of DL

SNR (DB)	BER
2	0.5613
6	0.4065
10	0.1853
14	0.0376

Table 3.1 BER VS SNR of DL

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VI Jun 2023- Available at www.ijraset.com

B. Simulation Parameters

PARAMETERS	VALUES
Cyclic Prefix	64
Type of Modulation	QPSK
Mini-Batch Size	8
Maximum Number of epoches	300
Maximum Doppler Frequency	200HZ

Table 3.2 simulation parameters of DL

BER vs. SNR for DL channel estimation shows that higher SNR is needed to get better BER, because BER value decreases as SNR increases. The lower the BER value, the better the communication.

C. BER VS SNR Comparison

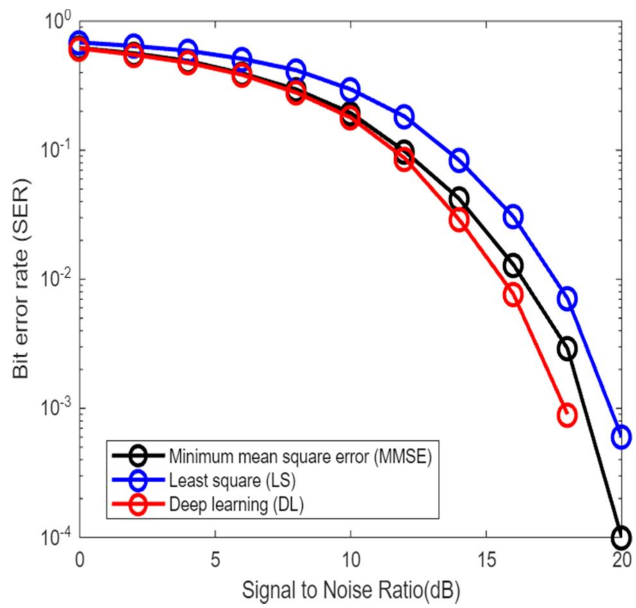

Fig 3.2 BER VS SNR OF LS, MMSE and DL

SNR (DB)	2	6	10	14
BER(LS)	0.6444	0.5169	0.2923	0.0839
BER(DL)	0.5613	0.4065	0.1853	0.0376
BER(MMSE)	0.5511	0.3826	0.1716	0.0293

Table 3.3 BER VS SNR OF LS, MMSE and DL

Simulations were performed and the results were compared with traditional LS and LMMSE estimations using bit error rate(BER) versus signal-to-noise ratio (SNR) as a measure. Each method of channel estimation steadily decreases the BER as theSNR increases. In both cases, the LS estimation gives the worst BER performance because no statistical channel information is considered when estimating the channel. In contrast, LMMSE estimation uses the mean and covariance matrices, resulting inbetter BER performance than LS estimation. The proposed deep learning algorithm provides the best MSE performance especially at low and medium SNR values.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VI Jun 2023- Available at www.ijraset.com

IV. CONCLUSION

When training the proposed DNN-based channel estimation method, the relevant full channel and least-squares channel estimation are used. By applying a QPSK modulation scheme, the performance of a given estimate is compared with traditional LS and LMMSE estimates in terms of channel estimation error and BER as a function of SNR level. With a correct understanding of the channel characteristics, we find that the proposed DNN-based estimation has good advantages in terms of minimizing the channel estimation error.

REFERENCES

[1] T. Van Chien and E. Bjornson, "Massive MIMOcommunications," in 5G Mobile Communications. Springer, 2017, pp. 77-116.
[2] E.Bjornson, N.Jalden, M.Bengtsson, and B. Ottersten, "Optimality" properties distributed strategies, andmeasurement-based evaluation of coordinated multicell OFDMA transmission," IEEE Trans. Signal Process., vol. 59, no. 12, pp. 6086–6101, 2011.
[3] E. Dahlman, S. Parkvall, and J. Skold, 5G NR: The next generation wireless access technology. Academic Press, 2018.
[4] S. Kay, Fundamentals of Statistical Signal Processing:Estimation Theory. Prentice Hall, 1993.
[5] J. Zhu, O. Omomukuyo, R. Venkatesan, C. Li and O. A. Dobre, "Rf-pilot phase noise compensation for long-haul coherent optical OFDM systems," 2015 IEEE 14th Canadian Workshop on Information Theory (CWIT), St. John's, NL, Canada,2015,pp. 127-130, doi: 10.1109/CWIT.2015.7255168.
[6] T.JIACHIN Least-Squares Channel Estimation for Mobile OFDM Communication on Time Varying Frequency-Selective Fading Channels[A]. IEEE 2008,57(6) : 3538-3550. [7] COLERI S, ERGEN M, Puri A Channel estimation techniquesbased on pilot arrangement in OFDM systems[J]. IEEE Trans.on Broadcasting, 2008,48 (3) :223 229.
[7] [8] J. Schmidhuber, "Deep learning in neural networks: An overview," Neural Network, vol. 61, pp. 85–117, Jan. 2015. [9]J.-M. Kang, C.-J. Chun, and I.-M. Kim, "Deep-learning-based channel estimation for wireless energy transfer," IEEE Communications Letters, vol. 22, no. 11, pp. 2310–2313, 2018.
[8] Yi Gong and K.B Lataief, "Low rank channel estimation for space-time coded wide band OFDM systems", IEEE Vehicular Technology Conference, vol. 2, pp. 772-776, 2001. 53
[9] D. Neumann, T. Wiese, and W. Utschick, "Learning the MMSE channel estimator," IEEE Trans. Signal Process., vol. 66, no. 11, pp. 2905–2917, 2018.
[10] T. O'Shea and J. Hoydis, "An introduction to deep learningfor the physical layer," IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563–575, 2017.
[11]] E. Dahlman, S. Parkvall, and J. Skold, 5G NR: The nextgeneration wireless access technology. Academic Press, 2018.
[12] Jaipreet Kaur1, Hardeep Kaur2, Manit Sandhu "OFDM: Comparison with Multicarrier Techniques and Applications", Volume 3, Issue 4 ,2016.
[13] K. Mei, J. Liu, X. Zhang, and J. Wei, "Machine learning based channel estimation: A computational approach for universal channel conditions," arXiv preprint arXiv:1911.03886, 2019.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue VI Jun 2023- Available at www.ijraset.com

[10] P. Hoeher, “A statistical discrete-time model for the WSSUS multipath channel,” IEEE Transactions on vehicular technology, vol. 41, no. 4, pp. 461–468, 1992. [17] Y. S. Cho, J. Kim, W. Y. Yang, and C. G. Kang, MIMO-OFDM wireless communications with MATLAB. John Wiley & Sons, 2010.
[18] G. T. 38.211, “Nr; physical channels and modulation,” 2017.
[19] S. N. Premnath, D. Wasden, S. K. Kasera, B. Farhang- Boroujeny, and N. Patwari, “Beyond OFDM: Best-effort dynamic spectrum access using filterbank multicarrier,” in Proc. 4th Int. Conf. Commun. Syst. Netw. (COMSNETS), Bengaluru, India, 2012, pp. 1–10.
[20] G. Fettweis, M. Krondorf, and S. Bittner, “GFDM—Generalized frequency division multiplexing,” in Proc. IEEE 69th Veh. Technol. Conf. (VTC), Barcelona, Spain, Apr. 2009, pp. 1–4.