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PERFORMANCE ENHANCEMENT OF THE CHANNEL ESTIMATION VIA DEEP LEARNING

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ABSTRACT

Channel estimation is a crucial task in wireless communication systems to accurately estimate the wireless channel's characteristics. Traditional methods for channel estimation often rely on mathematical models and assumptions, which may not capture the complex and dynamic nature of real-world channels. In recent years, deep learning techniques have demonstrated significant potential in diverse domains, including wireless communications. In this paper, a deep learning-driven framework for channel estimation is developed. This approach uses deep learning techniques with the Least Square (LS), or with Element-Wise-Minimum Mean Squared Error (EW-MMSE) methods. The selection of these methods highlights their simplicity, effectiveness, and compatibility with deep learning models. The profound learning capacity of Deep Neural Networks (DNNs) is used to understand the relationship between detected signals and the corresponding channel parameters. By formulating the channel estimation problem as a regression task, a DNN was trained to reduce the Mean Square Error (MSE) between the estimated and actual channel parameters. The simulation results of this work provide convincing evidence that the proposed approach is effective. Comparing the proposed approach with classic methods reveals its superior performance in terms of robustness to noise and computational efficiency. It achieves lower complexity than the exact Minimum Mean Square Error (MMSE).

KEYWORDS: Deep Learning, Channel Estimation, OFDM, LS, EW-MMSE.

تحسين أداء تقدير القناة عبر التعلم العميق

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الملخص

تقدير القناة هو مهمة حاسمة في أنظمة الاتصالات اللاسلكية لتحديد خصائص القناة اللاسلكية بدقة. غالبًا ما تعتمد الطرق التقليدية لتقدير القناة على النماذج الرياضية، والتي قد لا تستوعب الطبيعة المعقدة والديناميكية للقنوات في العالم الحقيقي. في السنوات الأخيرة، أظهرت تقنيات التعلم العميق نتائج واعدة في مجالات مختلفة، بما في ذلك الاتصالات اللاسلكية. هذا البحث، يقترح نظام قائماً على التعلم العميق لتقدير القناة. يستخدم النظام المقترح تقنية التعلم العميق مدمجة مع طريقة ال Least Square أو طريقة ال Element-Wise-Minimum Mean Squared Error حيث نستخدم امكانيات الشبكات العصبية العميقة (DNNs) لايجاد العلاقة بين الإشارة المستقبلة ومتغيرات القناة المقابلة. من خلال صياغة مشكلة تقدير القناة ك regression task، نقوم بتدريب DNN لتقليل متوسط الخطأ التربيعى بين متغيرات القناة المقدرة والحقيقية. تقدم نتائجنا التجريبية أدلة قوية على فعالية النظام المقترح من خلال مقارنته مع أساليب تقدير القناة التقليدية من حيث المتانة ضد الضوضاء، مع تقليل التعقيد مقارنة ب MMSE الدقيق.

الكلمات المفتاحية : التعلم العميق، تقدير القناة، OFDM، LS، EW-MMSE .

1. INTRODUCTION

The Fifth Generation (5G) is one of the latest generations of cellular networks that promises lower latency, faster data speeds, and higher capacity when compared to earlier versions. One of the key challenges of 5G is channel estimation. Channel estimation involves estimating the Channel State Information (CSI), including the gain and delay of each subcarrier in the Orthogonal Frequency Division Multiplexing (OFDM) symbol. The CSI is essential for the exact decoding of the received signal. Traditional channel estimation methods are often computationally complex and inaccurate in challenging channel environments. But deep learning models can extract complex patterns and relationships from extensive amounts of data by utilizing multi-layered neural networks. This capability makes deep learning attractive for channel estimation tasks, where the underlying channel characteristics can be highly non-linear and challenging to model analytically. Deep learning-based channel estimation methods have been shown to improve the data throughput and reliability of 5G systems when dealing with noise, interference, and blockages.

Moreover, OFDM is a modulation technique widely employed and serves as a cornerstone of the latest wireless communication systems, such as Wi-Fi, 4G/5G cellular networks, and digital broadcasting. It divides the available frequency spectrum into multiple orthogonal subcarriers, which are closely spaced and overlapping in frequency. Each subcarrier carries a part of the data, enabling the simultaneous transmission of multiple symbols [1].

The primary advantages of OFDM include robustness against frequency-selective fading, the ability to mitigate the Inter-Symbol Interference (ISI) arising from multipath propagation, and reliable spectrum use. By using the orthogonality of the subcarriers, OFDM enables efficient equalization and demodulation at the receiver, making it suitable for high-speed data transmission in challenging wireless environments [2]. Channel estimation via DNNs can be employed to estimate the channel parameters in OFDM systems. By training the DNN on labeled datasets containing known transmitted symbols and received signals, the network can learn to accurately predict the channel characteristics. This estimation can improve the equalization process at the receiver, leading to better signal recovery and decoding performance [3].

Deep learning has received much attention as a favorable tool in wireless communication in recent years. Regarding deep learning channel estimation, several schemes have been proposed in [3- 7].

The performance of deep learning receivers within frequency-selective fading environments of OFDM-based communication systems has been investigated using long-short-term memory (LSTM) for signal detection purposes in [3]. A deep learning-based approach for channel estimation that uses ChannelNet has been proposed in [4] and [5], and it is a viable alternative to the MMSE channel estimation scheme, but it takes longer to run. A deep learning-based channel estimation method that employs a DNN has been investigated in [6]. However, the proposed method necessitates multiple inputs to the DNN and encounters significant complexity. A DNN-aided estimation that minimizes the MSE between the channel estimate obtained by LS estimation and the actual channel is proposed in [7] to overcome the drawbacks of LS and MMSE estimations. But when the Signal to Noise Ratio (SNR) increases, the deep learning-based approaches yield a worse MSE compared to the performance of MMSE estimation. This may be due to the sub-optimal structure of the DNN models at high SNR levels.

Our study highlights the promising capabilities of deep learning techniques in the field of channel estimation in wireless communication systems. Using the profound learning capacity of deep neural networks, the precision and efficiency of channel estimation can be enhanced, thereby enhancing the performance of wireless communication systems in various implementations. A deep learning-based channel estimation method is proposed to correct LS and EW-MMSE channel estimation errors using DNN. The study demonstrates that the proposed method can accomplish significantly lower MSE than LS and MMSE with less complexity and compares the MSE of the proposed method with traditional channel estimation methods under different conditions. The results show that the proposed method is more robust to these conditions than traditional methods.

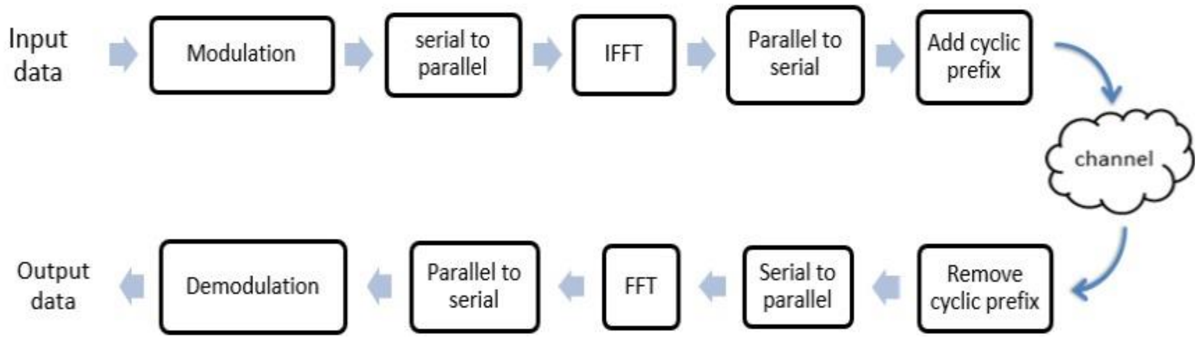

Fig. 1. OFDM transmitter-receiver block diagram.

The paper follows this structure. **Section 2** introduces the overarching framework of the system used in our study. **Section 3** is the mathematical description of the LS, EW-MMSE, and MMSE channel estimation methods. **Section 4** discusses the proposed channel estimation deep learning procedure. **Section 5** illustrates the simulation results. Then, the paper is concluded.

2. SYSTEM MODEL

The OFDM system is illustrated in Fig. 1, and the data input, denoted as s(t), is given by

$$s(t) = [\, s_1(t), s_2(t), ---, s_u(t)] \qquad (1)$$

where u is the number of the transmitted OFDM symbols. After converting the data from serial to parallel, a known pilot sequence is embedded within the data stream. The signal vector with the pilot sequence is denoted by $s_p(t)$. Next, the Inverse Fast Fourier Transform (IFFT) is applied to $s_p(t)$

$$s_{pt}(t) = IFFT\{s_P(t)\} \qquad (2)$$

To reduce the ISI, a Cyclic Prefix (CP) of length Kcp is added, resulting in the signal donated by s_{cp}(t). The received signal undergoes multi-path propagation in the 5G channel

$$y_{cp_u}(t) = H_u * s_{cp_u}(t) + z_u \qquad (3)$$

where $H_u \in \mathbb{C}^{K\times K}$ and $z_u \in \mathbb{C}^{K\times K}$ are the circular matrix standing for the channel and the additive white Gaussian noise, respectively.

Once the signal is received, the CP is removed using the CP removal module, resulting in the output vector $y_t(t)$. The parallel-converted signal, denoted by $y_{pt}(t)$, is subsequently transformed into the frequency domain using the Fast Fourier Transform (FFT), generating the frequency-domain signal $y_p(t)$given by the equation

$$y_p(t) = FFT\{y_{Pt}(t)\} \qquad (4)$$

The OFDM system model extracts a pilot signal from the frequency-domain signal to estimate the channel characteristics. Once the channel is estimated, the detected signal $y_p(t)$ is converted into a serial stream, donated by y(t). The final output is formulated as

$$y = s * h + z \qquad (5)$$

To estimate the channel gain, the preamble signal is formulated as

$$y_p = s_p * h_p + z_p \qquad (6)$$

3. CHANNEL ESTIMATION

The channel refers to the medium through which wireless signals propagate from the transmitter to the receiver. It is affected by numerous factors, such as multi-path fading, interference, and noise, which can degrade the quality of the received signal. Channel estimation aims to estimate the channel parameters, such as the complex gains and delays associated with different propagation paths. To mitigate the effects of these impairments, channel estimation is needed to compensate for the distortion introduced in the symbols as they travel through the channel and to consider the SNR. The procedure is done in this sequence. Firstly, establishing a correlation between the transmitted and received signals using the channel matrix demands the implementation of a mathematical model. Secondly, a known signal must be transmitted, and the corresponding detected signal must be detected. Thirdly, a comparison must be made between the transmitted signal and the received signal [8]. There are three types of estimators used in the channel estimation: MMSE, EW-MMSE, and LS, as described in **Table 1.**

Table1. Channel Estimation Techniques in Wireless Communication.

Technique	Operating Principle	Advantages	Disadvantages
LS	Solve a system of linear equations to estimate channel coefficients.	- Simple and computationally efficient. - Good for static channels.	- Sensitive to noise. - Performance degrades with multipath.
EW-MMSE	The full spatial correlation matrix is not required.	- Provides improved performance compared to the LS estimator. - Robust to noise and interference.	-There is a gap in the MMSE estimator where the error caused by pilot contamination has a high value.
MMSE	Minimizes the mean square error between the estimated and actual channels.	- Better performance than LS for noisy channels. - Manages multipath effectively.	- Higher computational complexity compared to LS and EW-MMSE estimation. - Requires knowledge of noise statistics.

3.1. MMSE estimator

The MMSE estimator is an optimal estimator that aims to reduce the average squared difference of the estimated value by considering the covariance between the observed data and the parameter to be estimated. The vector $\hat{h}$ represents the optimal estimate of h obtained using MMSE to reduce the error ϵ, where $\epsilon = E \|(h_p - \hat{h}_{p,MMSE})\|^2$, which estimates the current CSI h by making a comparison between a known pilot signal and the received UL signal y in (6). The Rayleigh-fading MIMO channel is the type of channel considered in this paper. The MMSE estimator is utilized to estimate the channel, where $\hat{h}_{P,MMSE} = A * y_p$.

$$A = R_{hp} \ (R_{hp} + s_p{}^{-1} R_{zp} \ s_p{}^{-H})^{-1} s_p{}^{-1} \quad (7)$$

Given that $R_{hp} = E\{ h_p h_p{}^H \}$ and $R_{zp} = E\{ z_p z_p{}^H \}$ are the channel and noise auto-correlation matrices, respectively.

$$A = R_{hp}\ (R_{hp}\ \ + \frac{I}{\beta})^{-1}\ s_p{}^{-1}, \text{ where } \ \beta = \frac{\mathrm{Ep}}{\mathrm{k} * \mathrm{No}} \tag{8}$$

and R_{hp} is the covariance matrix of h

$$\hat{h}_{p,MMSE} = R_{hp}\ \ (R_{hp}\ \ + \frac{I}{\beta})^{-1}\ s_p{}^{-1} * y_p \tag{9}$$

3.2. EW-MMSE estimator

This method is based on estimating each element of h individually. The EW-MMSE estimator does not require the full spatial correlation matrix. Instead, it considers several SNR values specified by β_u. The EW-MMSE estimator of h is the vector $\hat{h}$ that minimizes ϵ, where

$\epsilon = E \parallel (h_p - \hat{h}_{p,\,EW\text{-}MMSE}) \parallel^2$ and $\hat{h}_{p,\,EW\text{-}MMSE} = A_{EW} * y_p$

$$A_{EW}[u] = (R_{hp}\ (R_{hp}\ \ + \frac{I}{\beta_u})^{-1}\ (s_p{}^{-1})) \tag{10}$$

where $\beta_u = \frac{\mathrm{Ep}}{\mathrm{k} * \mathrm{No}}$ and R_{hp} is the covariance matrix of h

$$\hat{h}_{p,\,EW\text{-}MMSE} = R_{hp}(R_{hp}\ \ + \frac{I}{\beta_u})^{-1}\ (s_p{}^{-1}) * y_p \tag{11}$$

3.3. LS estimator

The LS aims to minimize the mean square error of the estimated value by assuming that the observed data is independent and identically distributed. This makes the LS estimator simple to calculate, but it can be less accurate than the MMSE or EW-MMSE estimators when the observed data is correlated or time-varying. In the absence of complete statistical knowledge, the LS estimator provides a practical approach for obtaining estimates. The LS estimate of h is given by $\epsilon_{LS} = E \parallel (h_P - \hat{h}_{p,LS}) \parallel^2$, where

$$\hat{h}_{p,LS} = y_p / s_p \tag{12}$$

4. THE DEVOLPED APPROACH

DNN is a promising approach for channel estimation in wireless communication systems, offering several advantages over other deep learning models, including flexibility, accuracy, efficiency, and adaptability.

4.1. DNN overview

A DNN is a deep learning model that uses multiple layers of interconnected neurons to process information [9]. DNNs have attained notable achievements across various fields, including wireless communication [10] and many other domains. In a DNN, neurons are organized into layers. The initial layer receives the raw data for processing. The subsequent layers, referred to as hidden layers, and the final layer, known as the output layer, generate the network's predictions or outputs. Each layer is interconnected with the next layer.

The fundamental building block of a DNN is the artificial neuron. Each neuron takes in multiple inputs, performs a weighted sum of these inputs, applies an activation function, and produces an output. By introducing non-linearity, the activation function equips the network to model complex patterns in the data.

Training a DNN involves a process called back-propagation [11], which combines forward propagation (passing data through the network) and gradient-based optimization. During training, the network adjusts the weights associated with each connection based on the error between its predictions and the true labels. This iterative process updates the weights, gradually minimizing the error and improving the network's performance.

Let I stand for the number of hidden layers in a DNN, with Q_i nodes for each layer, where $1 \leq i \leq I$ and $1 \leq q \leq Q_i$. Each node output is denoted as $y(i-1) \in \mathbb{R}^{Qi-1 \times 1}$, multiplying it by a weight vector $\omega(i, q) \in \mathbb{R}^{Qi-1 \times 1}$ and adding a bias b(i, q), The resulting value is then passed through an activation function f(i, q), generating the outcome

$$y\,(i, q) = f\,(i, q) * (b\,(i, q) + \omega\,(i, q)^{T} * y\,(i-1)) \qquad (13)$$

The aggregate output of the neurons in layer I is formulated as

$$y\,(i) = f\,(i) * (b\,(i) + W\,(i) * y\,(i-1)) \qquad (14)$$

where $W(i) \in \mathbb{R}^{Qi \times Qi-1}$, $b(i) \in \mathbb{R}^{Qi-1 \times 1}$ and f(i) stand for the connection weight matrix between layer (i − 1) and layer i, the intercept vector, and the activation function, respectively.

The training process for DNN involves adjusting weights and biases. After selecting a network architecture and initializing the weights, the network's output is calculated using forward propagation to obtain y(I). The error between the predicted output and the actual output is then determined using an appropriate loss function, Ψw,b. The gradient descent optimization method with backpropagation is used to reduce the error.

The objective is to minimize the variation between the actual output and the predicted output of the DNN. To reduce the cost function Ψw,b the backward propagation technique is used, employing various optimizers. These optimizers iteratively update the values of W and b during training. Various optimizers can be utilized, such as stochastic gradient descent [12] and Adaptive Moment Estimation (ADAM). The updating rule for adjusting the values of W and b is as follows:

$$\omega\,(i, q)_{NEW} = \omega\,(i, q) - \rho \frac{\partial\, \Psi w,b}{\partial\, \omega(i,q)} \qquad (15)$$

where ρ stands for the learning rate.

4.2. Proposed DNN LS and EW-MMSE channel estimation methods

Leveraging deep learning algorithms recommends elevating the effectiveness of LS and EW-MMSE channel estimation. A deep neural network is employed to learn the relationship between the received signal and the estimated channel. The trained neural network can then be used to estimate the channel in real-time, even in low SNR regions.

LS and EW-MMSE channel estimation via deep learning combines the principles of LS and EW-MMSE estimations with deep learning algorithms to estimate channel parameters in communication systems.

The suggested approach leverages a DNN in conjunction with LS and EW-MMSE to accurately estimate the channel impulse response (h_p) from the received preamble. This approach strikes a remarkable balance between performance improvement and computational complexity reduction.

The proposed DNN aims to enhance the performance of the LS and EW-MMSE channel estimations by optimizing the cost function Ψw,b. The inputs of the DNN are the LS estimated channel $\hat{h}_{p,LS}$ and the EW-MMSE estimated channel $\hat{h}_{p,EW-MMSE}$, respectively. Firstly, the received preamble is processed using the LS and EW-MMSE channel estimation methods, respectively. Subsequently, both LS and EW-MMSE channel estimates are decomposed into their real and imaginary components, resulting in a total DNN input of $2|K_{on}|$.

Once the training process is complete, the DNN's output layer generates the refined LS channel estimate and the corrected EW-MMSE channel estimate, scaled to ensure a zero mean and unit variance. The DNN training employs the MSE loss function with the ADAM optimizer [13].

The ReLU activation function is applied throughout the DNN architecture. No activation function is applied in the output layer of the DNN to allow the output values to remain unrestricted. Two fundamental designs of the DNN are proposed, each with a distinct number of hidden layers and nodes per layer, as detailed in **Table 2**. It is evident from the results that our procedure can significantly enhance the performance of least square and EW-MMSE channel estimation.

5. SIMULATION RESULTS

5.1. Proposed approach performance

Herein, the impact of the proposed deep learning approach is assessed by estimating the channel using Normalized Mean-Squared Error (NMSE) and comparing it with the traditional methods. Each obtained result is also explained. The parameters required to configure the system are listed in **Table 2,** and the DNN model parameters are listed in **Table 3**.

Table 2. OFDM system design variables

Parameters	Values
Size of FFT	64
Length of CP	16
Number of subcarriers	64
Number of active subcarriers	52

Table 3. Parameters for DNN network

Parameters	Values
Hidden layers number (DNN1)	1
Hidden layers number (DNN2)	3
Neurons-number of each layer (DNN1),	52
Neurons-number of each layer (DNN2)	52
Activation function	RELU
Type of optimizer	ADAM
Cost function	MSE
Number of epochs	500
Batch size	32

The RTV Power Delay Profile fading channel model is used [14]. Among the sixty-four subcarriers of an OFDM symbol, only fifty-two are active. The proposed approach is compared to the LS and exact MMSE procedures concerning their performance.

Figs. 2 and **3** display the NMSE performance of the different channel estimation methods considered in various scenarios. LS produces the least satisfactory results compared to the other methods. LMMSE estimation performs better than LS in terms of MSE. Our deep learning approach achieves the lowest MSE, and even at SNRs greater than 15 dB, it continues to perform well.

The performance of our deep learning method is dependent on the SNR used during training. Employing the highest expected SNR during training yields optimal performance. However, training at an extremely high SNR still provides reliable performance. The figures demonstrate that the CP significantly reduces the NMSE values. The CP allows for easy separation of the OFDM symbol from its delayed copies, simplifying the channel estimation process and leading to better equalization and demodulation, resulting in lower MSE.

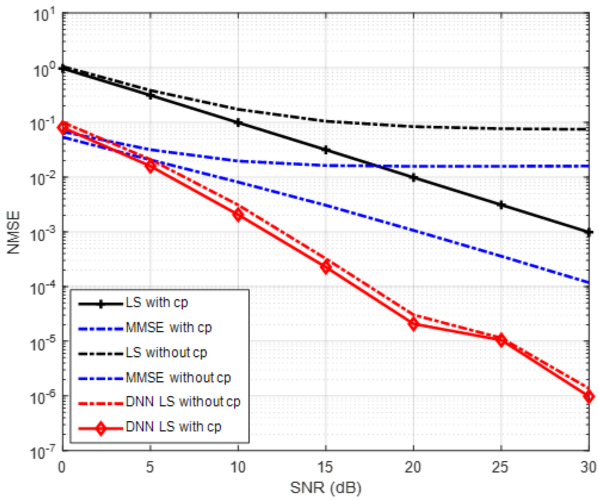

Fig. 2. NMSE versus SNR with DNN trained at SNR = 30dB.

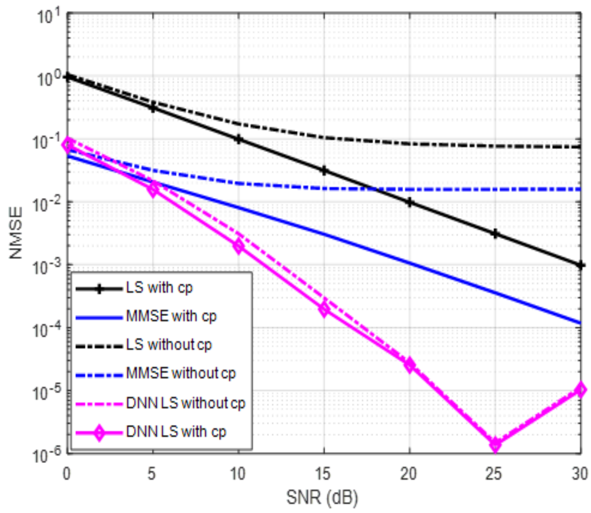

Fig. 3. NMSE versus SNR with DNN trained at SNR = 20dB.

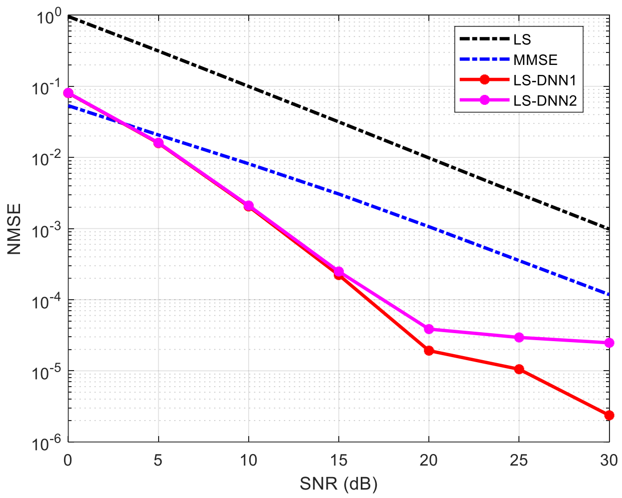

Fig. 4. NMSE versus SNR for different DNNs.

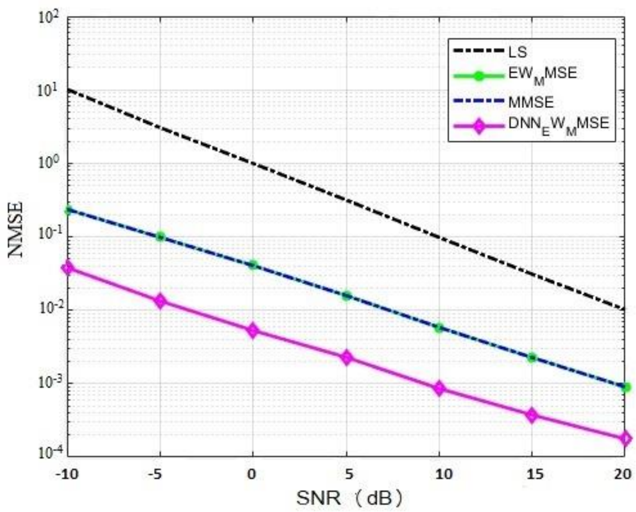

Fig. 5. NMSE versus SNR.

Fig. 4 shows that while DNN2 has more hidden layers than DNN1, DNN1 achieves better accuracy. This suggests that DNN complexity does not guarantee accuracy.

Fig. 5 displays straightforward evidence of the impact of our introduced method. It shows that the DNN-EW-MMSE gives the best performance compared with the traditional methods, especially at low SNR.

5.2. Computational Complexity

The number of multiplications is a crucial metric for selecting efficient DNN architectures and training algorithms. Computing all neuron activations in each layer is necessary. When transitioning from the i layer to the (i-1) layer, $M_{i-1}M_i$ multiplications are needed [15], [16]. The additional operations in a DNN are straightforward. Thus, the overall count of multiplications within a DNN formulated as

$$M_{total} = \sum_{i=1}^{I} M_{i-1}M_i \qquad (16)$$

The overall count of multiplications of the proposed DNN approaches is $4|K_{on}|^2$. For DNN1 and $6|K_{on}|^2$ for DNN2. The computational complexity of an accurate LMMSE channel estimation scheme is of order $|K_{on}|^3$.

Based on the information provided above, the complexity of the proposed system is lower than that of MMSE.

Conclusions

Our proposed approach involves the implementation of DNN for channel estimation, utilizing the estimation of SNR at the receiver. The concept of DNN is introduced, and a deep learning-based channel estimation method is presented. It is evident from the results that the proposed method accomplishes superior achievement than exact MMSE channel estimation with lower computational complexity. The adaptability of the DNN model to diverse channel environments positions it as a valuable tool for next-generation communication systems that demand flexibility and efficiency. One can consider the optimization of DNN architectures, investigate transfer learning techniques for different communication scenarios, and consider the integration of real-world data for further validation. As we move towards the era of intelligent and adaptive communication systems, the integration of DNNs holds great promise for enhancing the reliability and efficiency of channel estimation in diverse and challenging environments.

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