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Deep Learning-Based Signal Constellation for OFDM Underwater Acoustic Communications

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Keywords:
Complexity; Deep learning; OFDM; Signal constellation; Underwater acoustic communications.

Highlights:
- *Zero cyclic prefix (CP) based OFDM.*
- *Constellation algorithm based on supervised deep learning.*
- *Applicable in underwater acoustic communications.*
- *Bandwidth efficient for the underwater environment.*
- *Reduced complexity compared with MMSE and LS.*

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Abstract: The application of deep learning (DL) techniques to optimize signal constellations in communications using orthogonal frequency division multiplexing (OFDM) has shown potential. This novel approach utilizes network capabilities to create tailored signal constellations well suited for underwater conditions. The main objectives of this research are to enhance the effectiveness and dependability of data transmission in channels by adapting these signal constellations without adopting cyclic prefix, which can exploit the inherent bandwidth limitation effectively. The most prominent finding from this research is that even with zero cyclic prefix (CP) and a few pilot samples Np, inserted ahead of N subcarriers, the proposed signal constellation algorithm based on supervised DL attains a stable profile. Thus, it offers more bandwidth and reduces the complexity. The hegemony was depicted in the performance of the bit error rate (BER) of the proposed DL-based signal constellation prediction algorithm, which achieved 100% accuracy and a gain of 10dB and 12dB over minimum mean square error (MMSE) and least square (LS) channel estimation performance, respectively, when $CP = 0$ at $N_p = N/4$. Ultimately, this work contributes to increasing the performance of communication systems for applications such as exploration, monitoring, and data collection.

كوكبة الإشارات المعتمدة على التعلم العميق للأنظمة متعددة الارسال في التردد المتعامد للاتصالات الصوتية تحت الماء

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الخلاصة

لقد أظهر تطبيق تقنيات التعلم العميق إمكاناته لتحسين مجموعات الإشارات في الاتصالات باستخدام الأنظمة متعددة الارسال في تقسيم التردد المتعامد. يستخدم هذا النهج الجديد قدرات الشبكة لإنشاء مجموعات إشارات مصممة خصيصًا ومناسبة تمامًا للظروف الموجودة تحت الماء. الأهداف الرئيسية لهذا البحث هي تعزيز فعالية وموثوقية نقل البيانات، في القنوات من خلال تكييف مجموعات الإشارة هذه دون اعتماد بادئة دورية، والتي يمكنها استغلال قيود عرض النطاق الترددي المتأصلة بشكل فعال. النتيجة الأكثر وضوحًا التي تم التوصل إليها من هذا البحث هي أنه حتى مع وجود بادئة دورية صفرية وعدد قليل من العينات التجريبية، التي تم إدراجها قبل الموجات الحاملة الفرعية، فإن خوارزمية كوكبة الإشارة المقترحة المستندة إلى التعلم العميق الخاضع للإشراف تصل إلى ملف تعريف مستقر. لذلك، تتيح هذه الخوارزمية عرض حزمة اكبر و اقل تعقيداً. يتم تصوير الهيمنة في أداء معدل خطأ البتات لخوارزمية التنبؤ بكوكبة الإشارة القائمة على التعلم العميق المقترحة، والتي تحقق دقة بنسبة ١٠٠٪ وكسب ١٠ ديسيبل و١٢ ديسيبل على الحد الأدنى لمتوسط الخطأ المربع وأداء تقدير القناة المربعة الأقل، على التوالي، مقابل صفر البادئة الدورية وطول الدليل هو ربع الموجات الحاملة الفرعية. وفي نهاية المطاف، يساهم هذا العمل في زيادة أداء أنظمة الاتصالات لتطبيقات مثل الاستكشاف والمراقبة وجمع البيانات.

الكلمات الدالة: التعلم العميق، الأنظمة متعددة الارسال في تقسيم التردد المتعامد، كوكبة الإشارات، الاتصالات الصوتية تحت الماء، التعقيد.

1.INTRODUCTION

The growing demand for data transfer in communication systems has created a need for intelligent signal processing methods. Machine learning (ML) algorithms have proven effective in many engineering fields. ML algorithms excel at identifying system characteristics and capturing real-world imperfections due to their reliance on data. Neural networks (NNs) have proven highly effective in estimating channels. However, DL algorithms often come with requirements that increase the complexity of communication systems. Moreover, deep learning networks typically consist of neurons distributed across layers, necessitating a volume of training data to achieve the intended result. Blind modulation classification (BMC) techniques for OFDM fall short of meeting the performance standards by relying on statistical methods [1]. As a result, the modulation classification research community is exploring the integration of learning (DL) approaches to enhance modulation classification accuracy. However, many existing DL methods for automatic modulation classification (AMC) of OFDM that depend on extracting features from the signal encounter challenges in adapting to changes in signal parameters within adaptive transceiver systems. A new method for addressing this problem involves an AMC solution designed for OFDM systems. This solution utilizes a network (CNN) with learning. The innovative AMC approach allows for the recognition of the modulation format in received OFDM signals when there are fluctuations in the number of subcarriers and randomization in carrier frequency offset (CFO) symbol timing offset (STO). In the realm of 5G and upcoming 6G systems, cognitive radio (CR) technology plays a role in managing spectrum resources due to the abundance of radio frequencies available. Blind modulation recognition (BMR), an aspect of CR technology that significantly enhances efficiency, was proposed by [2]. However, there is a lack of focus on BMR research in MIMO OFDM systems. Leveraging the advancements in learning, an approach called series constellation multi-modal feature network (SC MFNet) was introduced to identify modulation types on MIMO OFDM subcarriers. By utilizing a blind signal separation algorithm without knowledge, the distorted transmitted signal was reconstructed. Zhang et al. [3] introduced a DL-based receiver for acoustic UWA communications using OFDM. The model was tailored to suit the complexities of UWA communications by utilizing a network with skip connections for signal recovery. Leveraging stacks of layers with connections enabled the effective extraction of meaningful features from incoming signals and reconstructing the original transmitted symbols. The performance was validated using training and testing data generated from the WATERMARK dataset collected at sea. The results of the experiments were demonstrated using the least squares channel estimation. Qin et al. [4] explored the developments in learning for physical-layer communications. It focused on the difficulties faced by systems and how deep learning can address them. The article also examined the advantages of incorporating knowledge into learning models and showcased instances where it enhanced communication system performance. Lastly, the paper proposed research avenues to advance communications at the physical layer. Jebur et al. [5] explored the possibility of creating machine learning techniques for channel estimation in 6G communications. The suggested algorithm combined with frequency division multiplexing to remove inter-symbol interference. The article investigated the algorithms' resilience, intricacy, and convergence while showcasing the achieved outcomes. Furthermore, it delved into the applications of this research in communications. Furthermore, Zhang et al. [6] introduced an approach to estimate channels and detect signals in cyclic prefix-free (CP-free) OFDM systems using a passing technique. The method, known as orthogonal approximate message passing (DLOAMP), is designed to be efficient in terms of resources and can accurately estimate the channel variation through training. The simulation results showed that DLOAMP outperformed algorithms when regarding high-order modulation. The adaptability of OAMP Net allows its parameters to be adjusted for each layer. This proposed method exhibited promising performance compared to channel state information (CSI) CP at SNR and even surpassed CE Net CP under conditions similar to those with low SNR. Additionally, the impact of a specific optimization technique known as "early stop" in implementing the proximal policy algorithm within the openai/spinningup library is presented in [7]. The main concept behind early termination methods is to assess the extent to which the policy changes during each update and avoid updates that lead to sudden and drastic policy changes. In this version of early stop, KLE Stop, the updates will be halted if the KL divergence between consecutive updates exceeds a predetermined threshold. Dos Santos Sousa et al. [8] did not consider the decoding of OFDM as it can be efficiently managed using a fast Fourier transform with complexity. Additionally, this approach reduces the search area and subsequently simplifies the networks' complexity. This paper aims to present a technique for estimating channels in OFDM systems that do not require a CP. Mohammed [9] created a simulated environment to assess the performance of OFDM under various channel conditions. Different models were utilized. Furthermore, a learning technique has been utilized to estimate the channel by leveraging data from training. Two types of channel models were utilized to compare their effectiveness. An endeavor to employ learning techniques in addressing wireless channels without requiring real-time training is presented in Ref [10]. The outcomes of the simulations demonstrate that deep learning models can achieve performance comparable to conventional methods when there is an adequate number of pilots in OFDM systems. Moreover, these models exhibited better performance, with a limited number of pilots, and they were CP-free. An algorithm utilizing neural networks (DNN) was introduced to support modulation [11]. Its goal was to select the transmission mode to maximize the achievable throughput. According to the simulation results, the suggested multi-layer SBL algorithm showed accuracy in channel estimation compared to other techniques. In terms of labels, ambient backscatter communication (AmBC) is presented as a promised solution in Ref. [12] for energy-cost-effective Internet of Things (IoT) systems with strict power and budget constraints. A label-assisted transmission (LAT) framework that eliminates the need to estimate channel state information (CSI) in an AmBC system was proposed. The framework involved sending two known labels from the tag before transmitting data and using a modulation-constrained (MC) expectation maximization (EM) algorithm for signal detection. The paper plays a role in 5G and future wireless communication systems. In the field of modulation classification in communications systems, researchers [13] have embraced a DL approach. Their study primarily aimed to explore the application of DL in modulation classification tasks within communications systems. By leveraging large amounts of data from these systems, DL eliminates the requirement for feature selection, thereby streamlining the entire process. Signal modulation identification (SMI) is key in OFDM systems. It is commonly achieved through feature extraction and machine learning. However, traditional methods have limitations when classifying signals and extracting features, making them impractical for OFDM systems. A DL approach using a network (CNN) has been proposed for SMI [14]. This method involves training the network with in-phase and quadrature (IQ) samples of OFDM signals and incorporating dropout layers to prevent overfitting. Experimental results demonstrated that this DL-based method achieved accuracy and consistency compared to techniques performing effectively across various datasets.

Existing modulation identification techniques rely heavily on feature extraction and machine learning classification algorithms, which face difficulties extracting inherent signal features, resulting in classification vulnerabilities. Traditional methods predominantly rely on approaches, which makes distinguishing between different modulation modes challenging. In addition, all a forementioned studies have concentrated on terrestrial Channels. However, for an underwater channel, Deep learning algorithms have requirements and necessitate a substantial volume of training data. This issue has prompted the authors to consider the potential of implementing a machine learning (ML) algorithm with complexity precisely calculated for underwater environment. Additionally, due to the band-limited nature of the underwater channel, a zero cyclic prefix was adopted to be well suited for such a nature.

2.SYSTEM AND DEEP LEARNING MODEL

In this scenario, a communication setup with two nodes exchanges information through a channel. To ensure communication without interference caused by the channel, a technique called frequency division multiplexing (OFDM) is utilized. This approach helps the authors to eliminate the effects of inter-symbol interference (ISI) that may occur due to the characteristics of the channel. Consider the i^{th} OFDM signal generated by performing inverse Fast Fourier transform (IFFT) of $X_i(k)$ with N subcarriers:

$$\boldsymbol{x_i(n) = \frac{1}{\sqrt{N_c}} \sum_{n=0}^{N_c-1} X_i(k) e^{j2\pi f_i(n)}} \qquad (1)$$

It is assumed that the signal is modulated using M-ary quadrature phase keying (QPSK) and transmitted over a multipath fading channel characterized by:

$$\boldsymbol{c(\tau, t) = \sum_{l=0}^{L-1} h_l(t)\delta[\tau - \tau_l(t)]} \qquad (2)$$

where $\{h_l(t)\}$ are the path amplitudes, $\{\tau_l(t)\}$ are the time-varying path delays, and L is the total number of paths [15]. The path delays, τ_l, and the gains, h_l, were assumed constant over the frame duration T. Once the channel in Eq. (2) is convolved with the transmitted signal in Eq. (1), the received signal is given as:

$$\boldsymbol{y = [y_1, \cdots, y_K], \in \mathbb{C}^{1\times K}} \qquad (3)$$

where K is the number of packets.

3.DL-BASED SIGNAL CONSTELLATION

This section briefly discusses the design of RNN cells that have been shown to outperform neural networks when dealing with long input data [16]. Then, the architecture of the proposed estimators based on learning will be presented.

3.1.LSTM Structure

The LSTM technique was developed to tackle the challenge of maintaining long-term information while accommodating short-term input variations. Figure 1 illustrates the architecture of an LSTM cell. This cell consists of three gates [17]: The input gate i_t is chosen when adding information to the cell, the forget gate f_t clears the contents of the cells, and the output gate o_t enables extracting information from the cell [18]. LSTMs can be mathematically represented as follows [19]:

$$\boldsymbol{i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i)} \qquad (4)$$

$$\boldsymbol{f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f)} \qquad (5)$$

$$\boldsymbol{o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o)} \qquad (6)$$

where x_t and σ are the current input at the time step t and sigmoid, respectively. While h_{t-1} denotes the previous time step $t-1$ of the hidden state. The cell state (C_t) is updated based on these gates and the current input (x_t), as follows:

$$\boldsymbol{C_t = f_t \odot C_{t-1} + i_t \odot (W_{xc}x_t + W_{hc}h_{t-1} + b_c)} \qquad (7)$$

Where $\odot$ denotes element-wise multiplication. The calculation of the candidate cell state update at time step t in an LSTM cell is represented by $W_{xc}x_t + W_{hc}h_{t-1} + b_c$. This update considers the influence of the input x_t and the previous cell state C_{t-1} on the cell state C_t with the wights W_{xc} and W_{hc}, determining their respective contributions strengths. The bias term b_c provides an offset to this combination. To ensure that the new cell state remains within the range of $[1, -1]$, a non-linear transformation is applied using the hyperbolic tangent function. The output of the LSTM cell at time t is computed as:

$$\boldsymbol{h_t = o_t \odot \tanh(C_t)} \qquad (8)$$

where tanh refers to hyperbolic tangent activation functions.

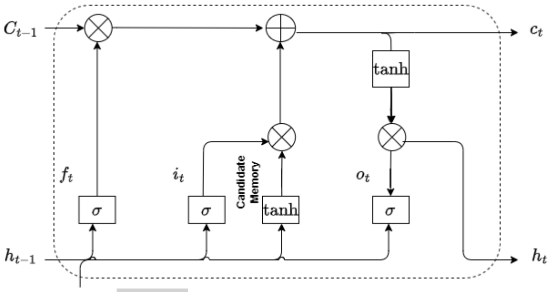


Fig. 1 LSTM Cell Structure.

3.2.The Proposed DL-based Signal Constellation Architecture

When learning is incorporated into utilizing the QPSK constellation, many of the equations used in digital communications are simplified within the process of data preprocessing and neural network structure. Nevertheless, there are still underlying concepts and mathematical representations that are important in this integration. For constellation learning, it is possible to normalize the I and Q components of the QPSK signal as:

$$\boldsymbol{I_n, Q_n = \frac{I-\mu_I}{\sigma_I^2}, \frac{I-\mu_Q}{\sigma_Q^2}} \qquad (9)$$

where the components I_n, Q_n are the normalized real and imaginary of I and Q, respectively, μ is the mean, and σ^2 is the noise variance. In tasks involving classification, like predicting QPSK constellation points, it is common to use the entropy loss as a frequently employed loss function. The cross-entropy loss is defined as;

$$\boldsymbol{L = -\sum_{c=1}^{M} y_{o,c} \log(p_{o,c})} \qquad (10)$$

where M is M-ary equal to the number of classes (4 in QPSK), y denotes the binary [1,0] if class label c is the correct classification for observation o, and p is the predicted probability that observation o is of class c. In the present work, an adaptive moment estimation (ADAM) optimization technique is adopted to optimize the layers wight W and the bias b. The architecture is shown in Table 1.

Table 1 Architecture Parameters.

Layer	Type of Layer	LSTM
L1	Input Layer	Sequence
L2	Hidden Layer 1	LSTM
L3	Output Layer	Softmax and Classifier

4.PROPOSED SYSTEM FOR SIGNAL CONSTELLATION

In this section, the proposed system's architecture and learning mechanism are introduced, based on a deep learning approach to predict signal constellations for underwater channels. Furthermore, the stages of the proposed system are illustrated, including data preparation, deep learning model training, and testing. These stages are visualized in Fig. 2.

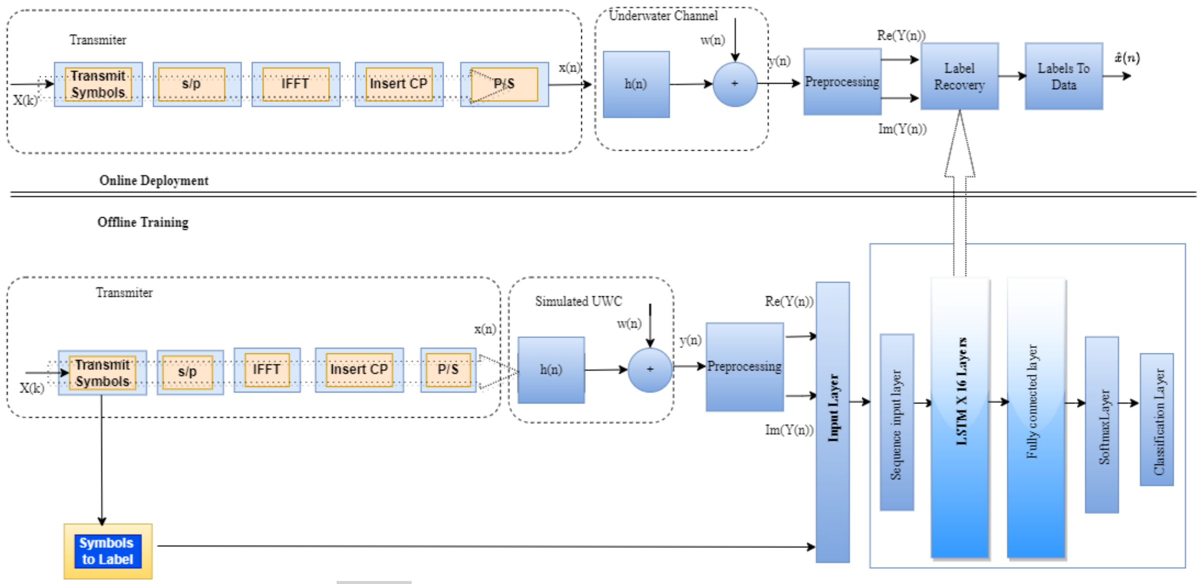


Fig. 2 System Model-Based Deep Learning.

4.1.Preparing Dataset and Training Models - Offline Stage

Preparing the datasets to be used to train the learning-based estimators is started in this phase. These estimators are trained offline. Then, in this stage, the trained estimators are utilized, along with their parameters, to make predictions for the channel. In Fig. 2, the pilots and data are fed into the OFDM transmitter to generate a series of n frames. These frames are then transmitted after being processed through the channel convolution. The pilots transmitted are then fed into an LS estimator to calculate an estimated channel. LS, which becomes one of the inputs, is used to train the estimators. During this research phase, the main focus is on the groundwork for effectively using deep learning techniques in underwater communication. This phase involves collecting and preprocessing a large amount of data, including acquiring acoustic channel data and creating training datasets. In Fig. 2, the transmitter includes input data along with pilots based on the input data $X(k)$ to produce $x(n)$. This transmitted signal convolved with the channel to produce $y(n)$. At the receiver front end, the preprocessing stage contains serial to parallel conversion, CP removal, and FFT. A set of real and imaginary parts for the entire packet, and the feature of the received packet are produced. These features are entered into the network to produce the constellation, as shown in Algorithm 1, the training and testing. Thus, the DL network deals with the real and imaginary parts values. The DL networks can be represented by the input vector as:

$$\boldsymbol{Y(n)} = [\Re(\boldsymbol{Y(n)}), \Im(\boldsymbol{Y(n)})] \qquad \textbf{(11)}$$

The target contains the formal QPSK constellation.

$$\boldsymbol{S(n)} = \left[e^{\frac{\pi}{4}}, e^{\frac{3\pi}{4}}, e^{\frac{5\pi}{4}}, e^{\frac{7\pi}{4}}\right] \qquad \textbf{(12)}$$

Underwater communication systems that utilize OFDM technology require carefully designed and improved specialized network architectures. These architectures provide a foundation for training and optimizing models that effectively adapt signal constellations to ensure data transmission performance in challenging underwater environments.

4.2.Online Stage

During this stage, the main focus revolves around applying learning models in real-time for underwater communication systems. In this stage, neural networks that have been trained play a role by adjusting signal constellations to adapt to the changing conditions encountered during data transmission. These conditions may include variations in channel characteristics, interference, and noise levels commonly found in environments. Through learning and optimization, the online phase aims to enhance the resilience, dependability, and overall efficiency of acoustic communications based on OFDM technology. The ultimate goal is to ensure the transmission and reception of data packets in challenging and unpredictable underwater scenarios. In this stage, a representation can be seen, as shown in Fig. 2. The trained parameters will be combined with the Test set to accurately determine the signal constellation using the trained data. Algorithm 1 provides an overview of the steps involved in training and testing signal constellations based on learning.

Algorithm 1: DL-Based Signal Constellation Algorithm

stage1: Offline Training
1. Generate data for the transmitted signal using x in 1 (Pilot, subcarriers, constellation).
2. Compute fading channel coefficient using 2.
3. Convert data to packet (pilot and data).
4. compute integer FFT for each packet.
5. insert CP.
6. Detect the received signal using 3 and 11.
7. convert tx pack and **rx** pack to features (target)
8. Formulate the transmitted packet to labels (Target).
9. combine data set to construct feature for DL algorithm to train the data set 80 and 20.
10. The DL algorithm consist of
    Inputlayer ← **1**
    LSTM ← **16** *Layers*
    Fullyconnectedlayer ← **4**
    Softmaxlayer
    Classification - outputlayer
11. Train the network
12. Save

stage2: Online Training
1. Load Trained network.
2. Convert received packet to feature.
3. Estimate constellation labels using DL classifier.
4. Convert label to constellation.

4.3. Data Set

For the constellation prediction task, a data set is generated with a QPSK modulation. This data set is used to verify the resilience of the proposed system. A range of signal-to-noise ratio (SNR) from 0 to 50 dB with a step of 5 dB is adopted, and data of 25000 packets per modulation symbol was used for training and testing. Considering the 128 OFDM subcarriers for data and 128 subcarriers for the pilot, there are 256 real and 256 imaginaries, respectively, i.e., 512 values to represent the feature of each received packet used. Thus, a large data set is input to the network for training or delivered in the online phase to predict the constellation.

5. COMPLEXITY ANALYSIS

This section compares the complexity of the proposed deep learning-based estimators with the MMSE estimator. To gauge the level of complexity, the number of floating-point operations (FLOPs) is adopted as a measure. Any operation involving two numbers, such as addition, subtraction, multiplication, and division, is viewed as a FLOP. The LSTM complexity can be approximated [20] as:

$$C_{LSTM} \approx \mathcal{O}(4h_s^2N)2 \tag{13}$$

where h_s and N denote the number of hidden layers and the number of subcarriers, respectively, considering the forward and backward propagation. Upon examination of equations (LS) and (LMMSE), it becomes evident that the LS estimator's complexity is of the order $\mathcal{O}(NP)$. Additionally, the complexity of the MMSE estimator can be represented as $\mathcal{O}(N^3)$ due to the calculations related to matrix inversion and vector multiplication. In Fig. 3, it is apparent that the complexity of the suggested algorithm and the MMSE estimator can be compared to the number of subcarriers (N). It becomes clear that as the quantity of samples rises, the complexity of the suggested algorithm will be notably less than that of the MMSE estimator.

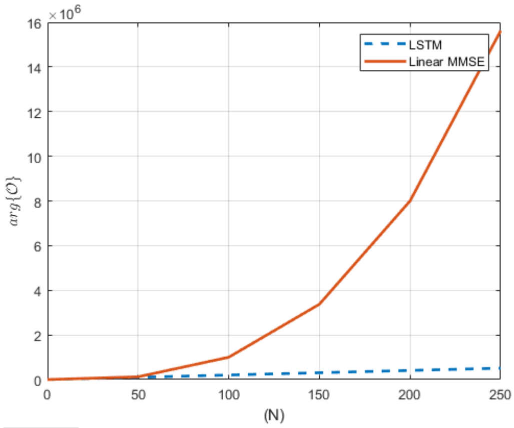


Fig. 3 Computational Complexity Comparison of ML Estimator and LMMSE.

6. SIMULATION RESULTS AND DISCUSSION

This section presents the results along with a discussion of the DL-based signal constellation performance for the underwater acoustic channel in the OFDM communication system. Basically, the simulation outcomes for all deep learning modeling, training, and testing in this section were achieved by utilizing the MATLAB 2022b Deep Learning Toolbox on an i7 processor operating at 1.8 GHz, coupled with an 8-GB RAM. Additionally, it is assumed that the suggested signal constellation algorithm based on DL was executed on the receiver node over an underwater channel model, as shown in Fig. 4. Furthermore, Table 2 provides an overview of the simulation and channel model settings.

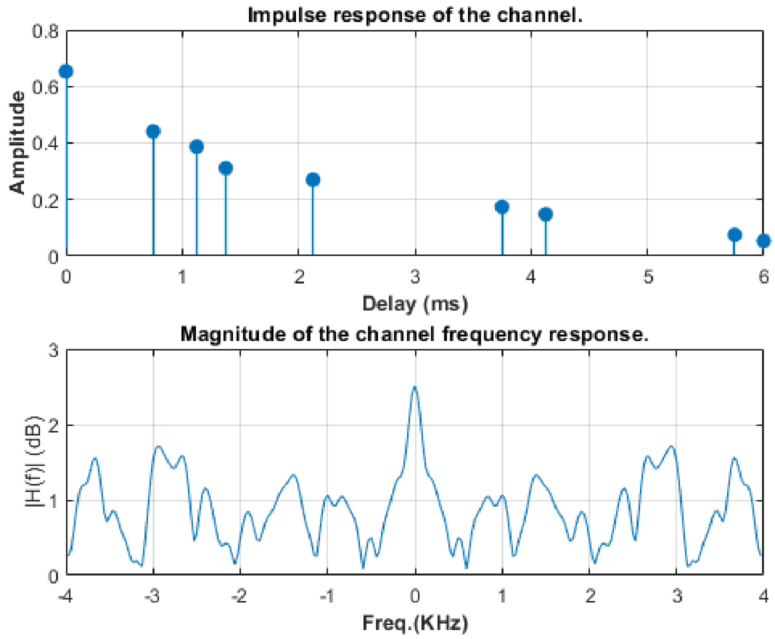


Fig. 4 Channel Characteristics.

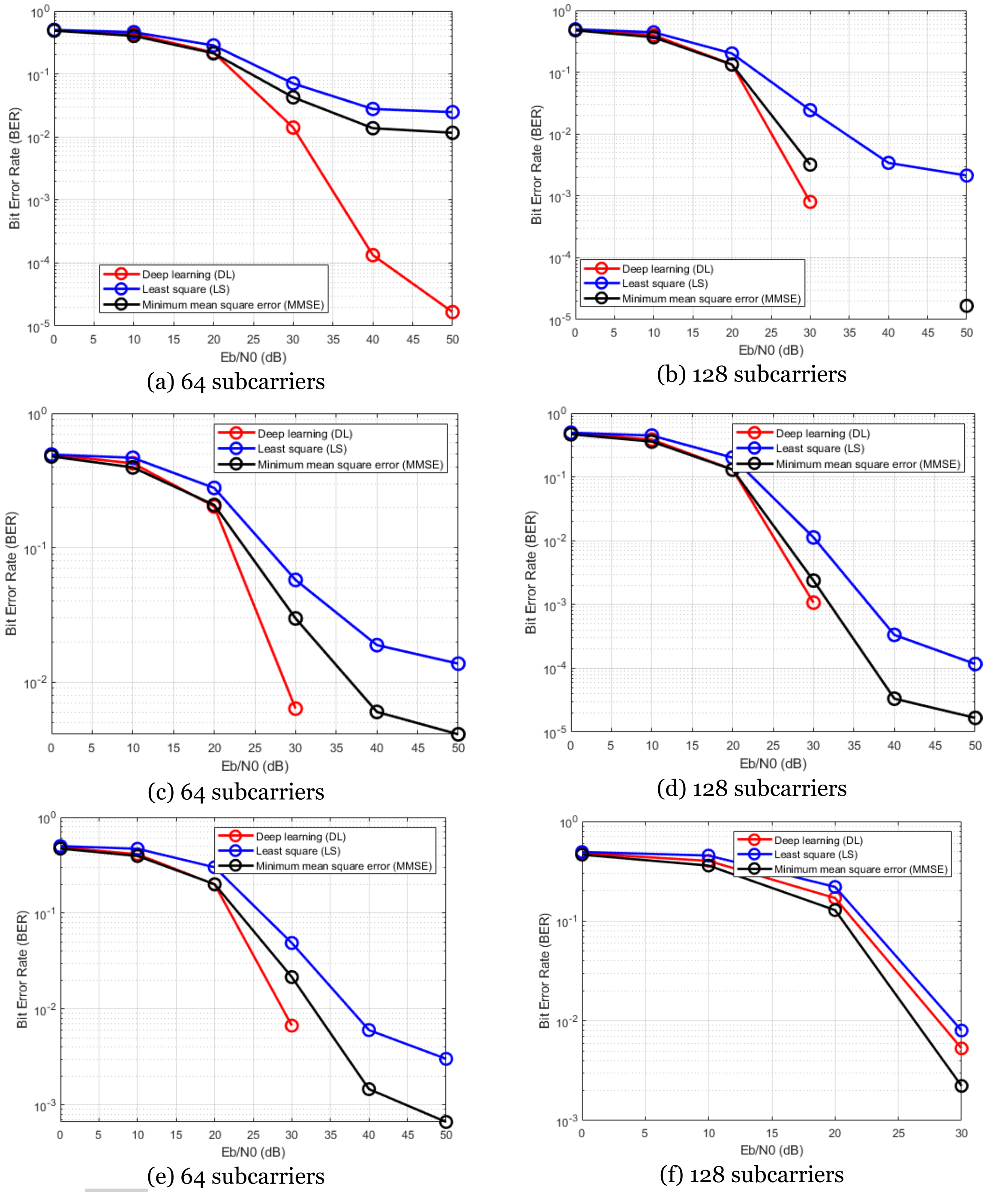
Table 2 Simulation and Channel Parameters.

Parameter	Value
Modulation Technique	QPSK
Channel Bandwidth	8kHz
Channel delay	6 ms
OFDM subcarriers (N)	64, 128
Pilot subcarriers (N_p)	$N_p = N, N_p = \frac{N}{2}, N_p = \frac{N}{4}$

6.1.Bit Error Rate (BER) Performance

In this section, the performance of a learning-based signal constellation in a multipath scenario was investigated. The effectiveness of this constellation with the LS and MMSE methods, specifically looking at the Bit Error Rate (BER), was compared. The present simulations kept network and training parameters consistent, except for varying the layer type depending on the DL-based estimator used. First, the MMSE and LS channel estimations were introduced to evaluate the BER of the proposed signal constellation-based DL for different pilot subcarriers at $N_p = N$, $N_p = \frac{N}{2}$, and $N_p = \frac{N}{4}$. Then, to test the effectiveness of the proposed DL system performance under a limited bandwidth underwater channel, two scenarios were conducted, $\text{CP} = 0$ and $\text{CP} = 16$, respectively. The first set of analyses examined the impact of pilot length on the BER performance when $\text{CP} = 0$. Figure 5 provides the results of the BER performance of the proposed DL with different subcarriers lengths at $\text{CP} = 0$. It is apparent from this figure that the DL outperformed MMSE and LS when the length of the pilots was less than N. This result is interesting and fits the underwater environment due to the bandwidth limitation nature. In Fig. 5 (a), where $N_p = \frac{N}{4}$, there is a clear trend of consistency in the performance of DL, as its performance stabilized when increasing N. On the other hand, it has been noticed that the performance of MMSE and LS was affected when the number of pilots was reduced. Interestingly, there is a correlation in the results shown in Fig. 5 (c) and Fig. 5 (e) that support the consistency of these results in which the MMSE and LS diverge when the number of pilot subcarriers is reduced. This behavior is because the channel estimation fails to estimate the channel accurately. In terms of complexity, reducing the number of pilots and subcarriers means reduced complexity, required for implementing embedded systems for other applications, such as 5G networks.
However, with successive increases in pilot subcarriers, the MMSE and LS converged further to the DL performance, as depicted in Fig. 5 (b), Fig. 5 (d), and Fig. 5 (f). It is more realistic because the MMSE accuracy increased once more when information came with CSI through the pilots. Turning to Fig. 5 (f), where $N_p = N = 128$, it can be noticed that the MMSE

outperformed the DL. This behavior occurred because the Bit Error Rate (BER) reached its saturation point, meaning that the performance of the signal constellation used in DL has already reached its potential. At this stage, there is no room for improvement. In Fig. 6, an improvement in deep learning performance was observed when increasing the cyclic prefix length despite increasing the number of subcarriers length. This improvement is a promising result and is inherent due to the presence of CP, protecting the frame from channel effects. Thus, increasing the CP length helped to reduce the errors caused by the channel. Compared to Fig. 5 (d) and Fig. 5 (f), it was noted in Fig. 6 (d) and Fig. 6 (f) that the performance of the proposed system improved despite the increase in the length of the pilots because the CP combats the channel length. Thus, it should be noted that the number of samples N_p required for the system to achieve performance levels equal to those of perfect CSI is contingent upon the delayed spread of the channel. This behavior is because the length of the channel vector was determined by the channel delay spread. This finding has important implications for developing an embedded DL algorithm for terrestrial channels in addition to underwater channels.



(a) 64 subcarriers

(b) 128 subcarriers

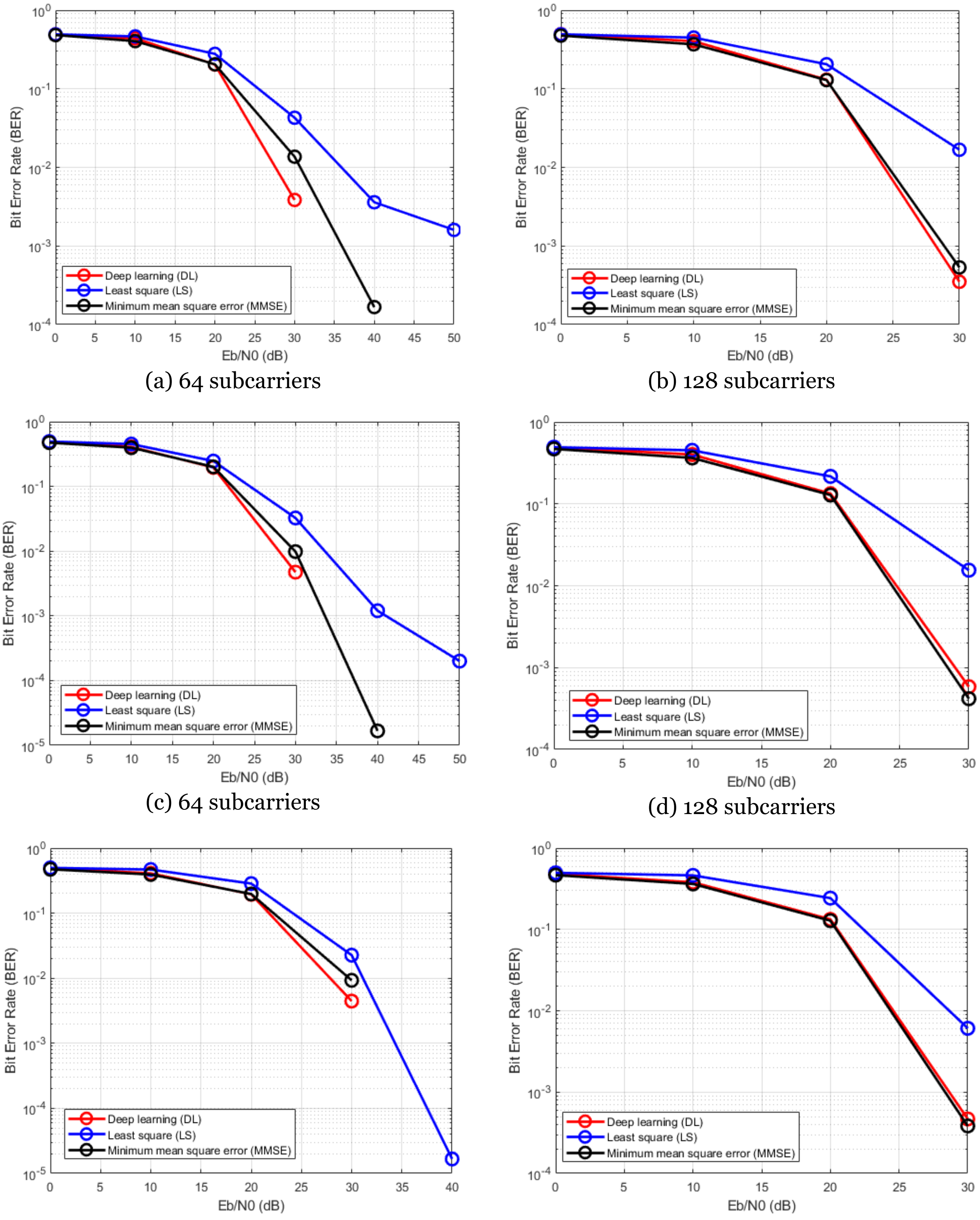
(c) 64 subcarriers

(d) 128 subcarriers

(e) 64 subcarriers

(f) 128 subcarriers

Fig. 5 BER at CP = 0 with Different Subcarriers and $N_p = \frac{N}{4}, N_p = \frac{N}{2}$, and $N_p = N$.



(a) 64 subcarriers (b) 128 subcarriers

(c) 64 subcarriers (d) 128 subcarriers

(e) 64 subcarriers (f) 128 subcarriers

Fig. 6 BER at CP = 16 with Different Subcarriers and $N_p = \frac{N}{4}, N_p = \frac{N}{2}$, and $N_p = N$.

6.2. Constellation Diagram

Figure 7 shows the constellation of MMSE at CP = 0. Based on the constellation diagrams, it appears that the MMSE channel estimation was quite effective in enhancing noise tolerance and improving the quality of constellations, especially when dealing with SNRs. The overall shape of the constellation resembles a square with four defined groups of points in line with QPSK modulation. However, there are variations from a square, especially at lower SNRs (10dB and 20dB), as shown in Fig. 7 (a) and Fig. 7 (b), which might be attributed to imperfections in the way the channel is estimated or how the modulation is performed. As the SNR increased from 30dB to 40dB, in Fig. 7 (c) to Fig. 7 (d), it was observed that the constellation points gathered closer to their positions. This behavior demonstrates enhanced resilience towards noise and a decrease in errors. Such behavior aligns with the authors' expectations for MMSE channel estimation.

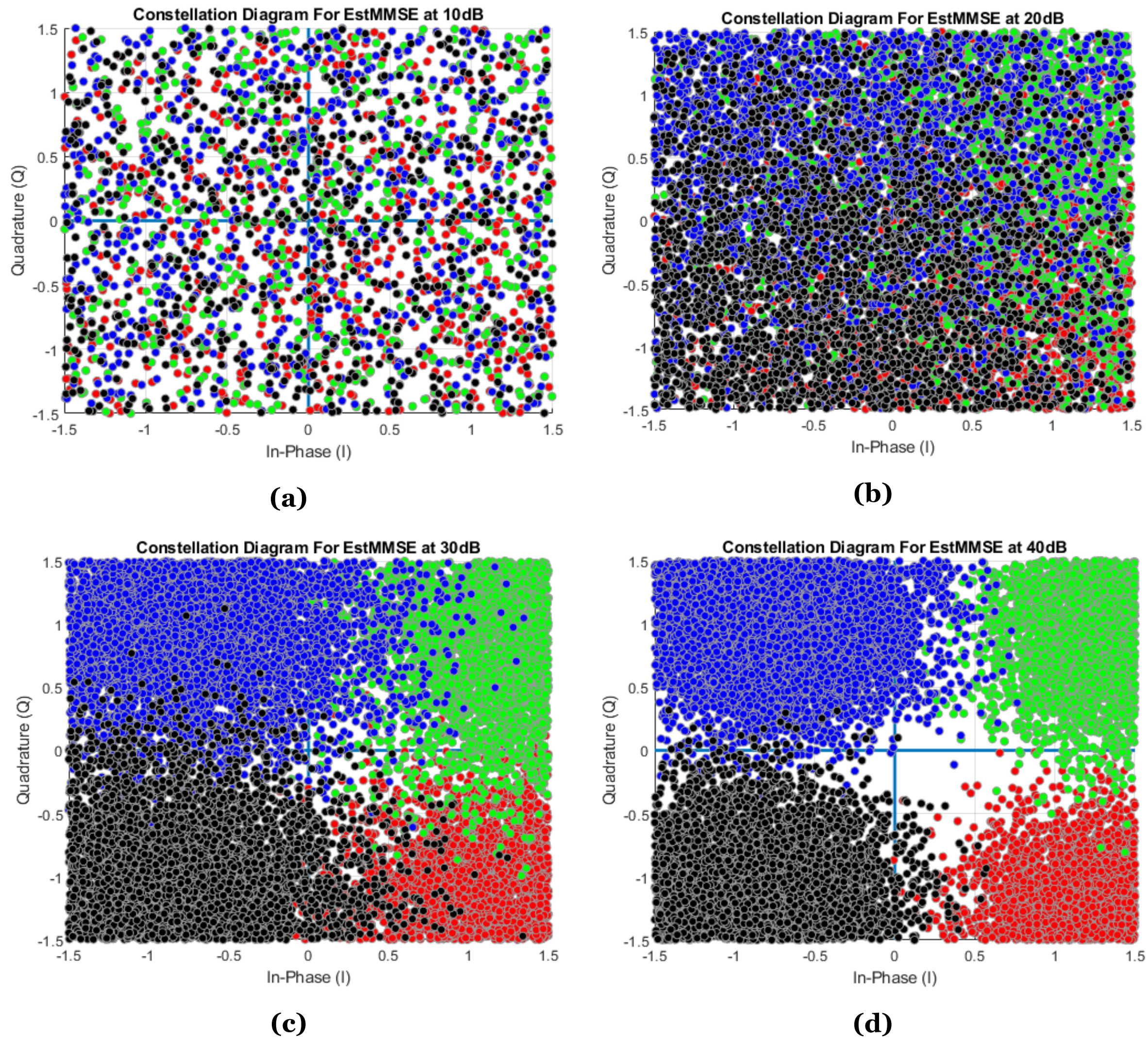
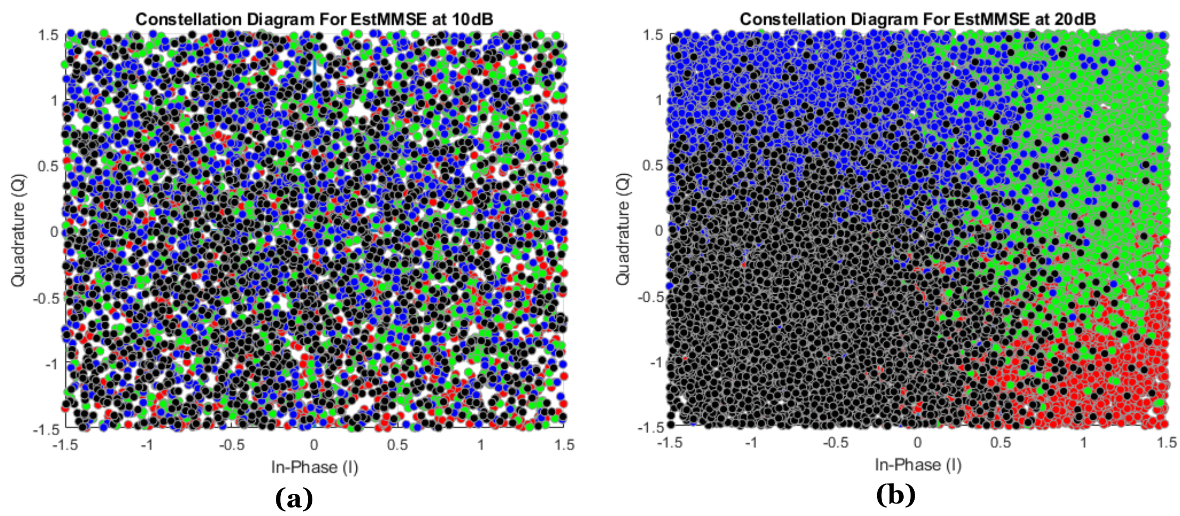
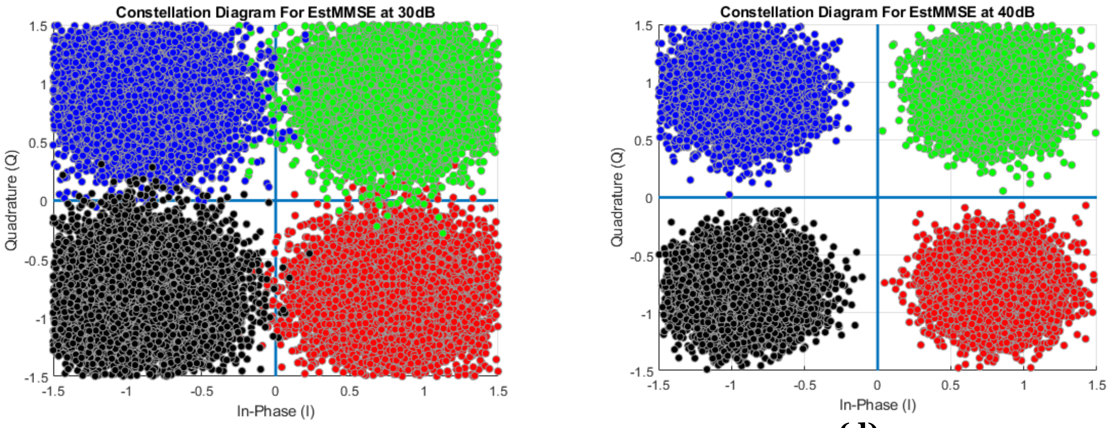


Fig. 7 Constellation Diagrams MMSE at 64 Subcarriers and $N_p = \frac{N}{4}$ with Different SNRs.





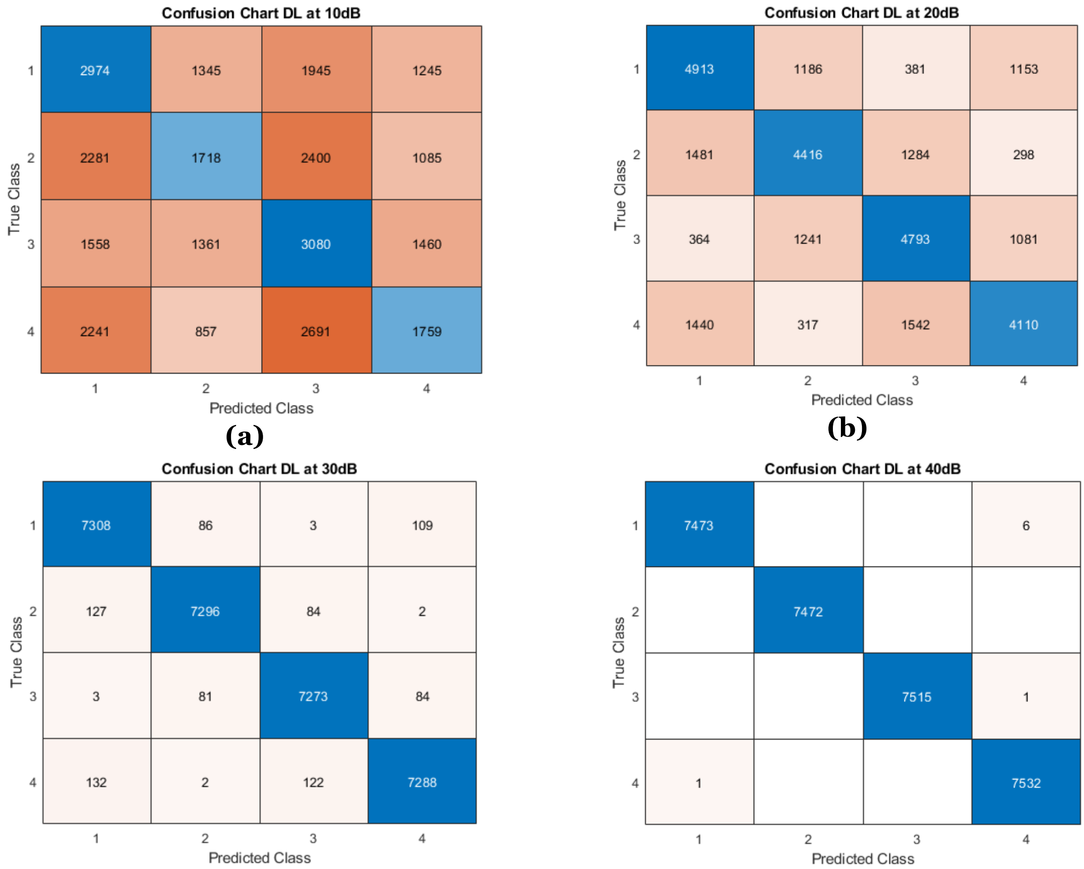
(c) (d)

Fig. 8 Constellation Diagrams MMSE at 128 Subcarriers and $N_p = \frac{N}{4}$ with Different SNRs.

It is important to note how the constellation points are packed together. As presented in Fig. 8, when using 128 subcarriers, the points will appear packed compared to when using 64 subcarriers. This distinction should be noticeable in SNRs where the clustering is more compact. The primary factor that distinguishes the constellation diagrams is the density of points. In the case of 128 subcarriers, three times many points will lead to a denser and more tightly packed constellation.

6.3.Confusion Matrix

The confusion matrix in Fig. 9 depicts the performance of the proposed DL at N =64 subcarriers. It can be shown from this figure that once the SNR was 10 dB, Fig. 9 (a), the performance was relatively low for all classes, with an accuracy of about 52%. An improvement was found between Fig. 9 (a) and Fig. 9 (b), in which the SNR was increased to 20dB, and the accuracy was raised to 74%. This behavior is because the escalation in the SNR escalates the achievement of class 1, and a better classification is obtained. Interestingly, an excellent classification ability was observed in Fig. 9 (c), with an SNR of 30 dB and an accuracy of 97%. Few off-diagonal elements were shown in this matrix, indicating minimal confusion between classes.



(c) (d)

Fig. 9 Confusion Matrices at 64 Subcarriers and $N_p = \frac{N}{4}$ with Different SNRs.

As shown in the previous analyses, Fig. 9 reinforces these results. As noticed when the SNR increased, the model's performance clearly improved. While the model performed exceptionally and achieved an accuracy of 99.9% when the SNR was 40dB, as shown in Fig. 9 (d), focusing on the remaining misclassifications and fine-tuning them will further increase the performance. Turning to analyze the confusion matrices in Fig. 10, in which the performance of the DL was evaluated at 128 subcarriers and $N_p = \frac{N}{4}$. Figure 10 (a), Fig. 10 (b), Fig. 10 (c), and Fig. 10 (d) represent the confusion matrices at 10dB, 20dB, 30dB, and 40dB, respectively. In Fig. 10 (a), where N =128, and the SNR was relatively low, the accuracy was about 36.5%. A comparison with Fig. 9 (a), in which N =64, revealed that at 10 dB, the model's performance noticeably declined as the constellation size (N) increased, indicating that the model had difficulty in discerning constellations, particularly when the SNR was low, and the number of subcarriers was high. With successive increases in SNR, the accuracy moved further to 87% and 99% at 20dB and 30dB in Fig. 10 (b) and Fig. 10 (c), respectively. A closer look at Fig. 10 (c), the matrix depicts a few elements off the diagonal, indicating little confusion between classes. The misclassifications that do occur involve several instances, typically in a single bit. In Fig. 10 (d), all the classes showed performance improvement, proving the model's capability to accurately differentiate between constellations at an SNR of 40 dB with a subcarrier size of 128. The matrix clearly indicated no elements outside the diagonal, confirming no confusion between the classes. In this scenario, the model's exceptional capabilities are showcased as it demonstrated performance in situations involving high SNR and extensive sets of subcarriers with $N_p = \frac{N}{4}$.

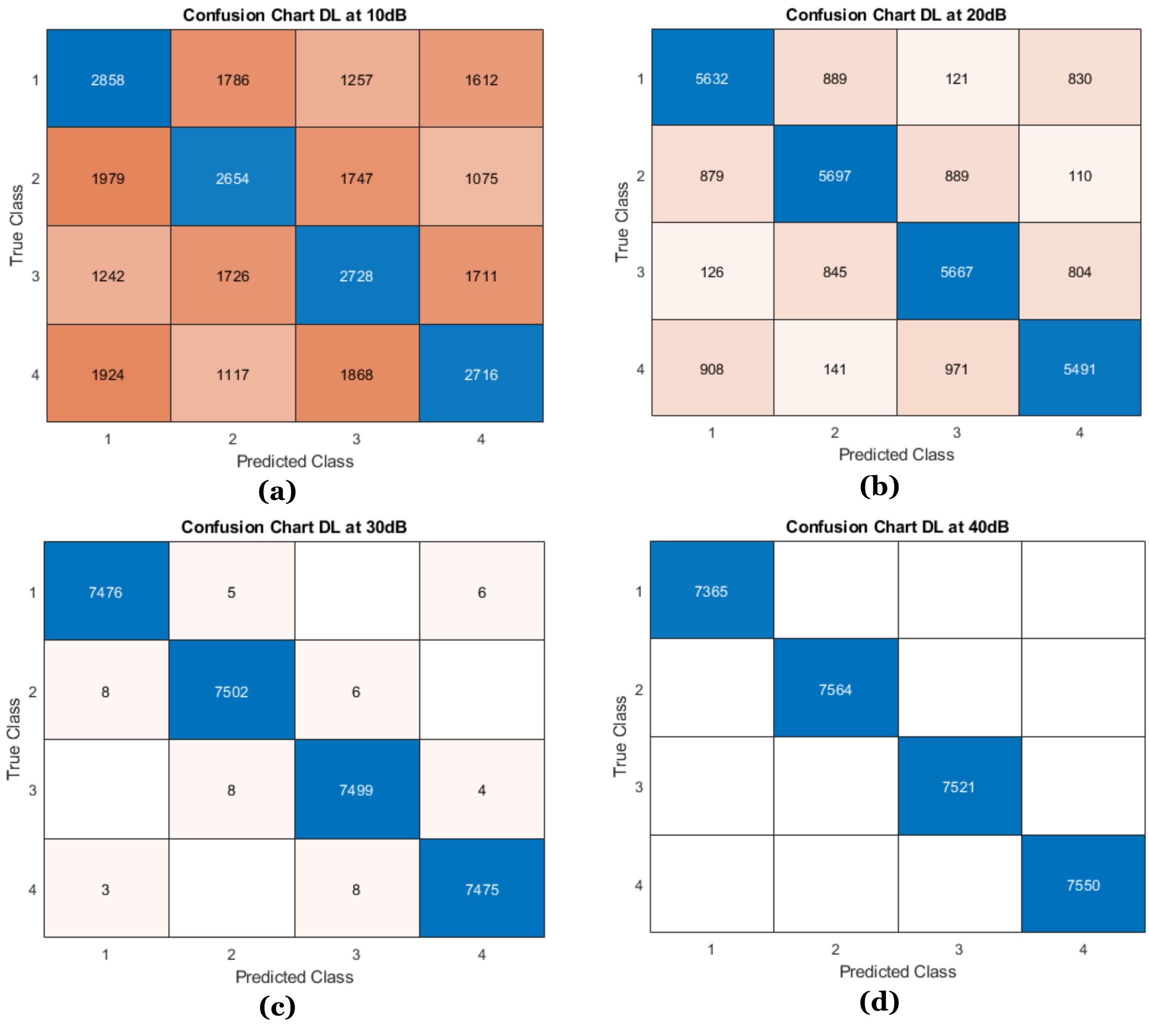


Fig. 10 Confusion Matrices at 128 subcarriers and $N_p = \frac{N}{4}$ with different SNRs.

7.CONCLUSION

In this study, a powerful supervised deep learning approach is introduced to predict signal constellations. The focus was on a system that uses an OFDM system to transmit data through a selective channel that varies over time. To begin, the performance of the suggested algorithm was assessed by measuring the MMSE and LS in channel estimation. The findings demonstrated that the DL algorithm outperformed LS and MMSE when using zero cyclic prefix and a small number of pilot samples with an accuracy of 100%. In particular, when $\mathrm{CP} = 0$ at $N_p = \frac{N}{4}$, the proposed DL-based signal constellation exhibited a BER performance gain of 10dB and 12dB compared to the MMSE and LS channel estimation algorithms. In addition, evaluating the complexity of the suggested deep learning algorithm was performed based on FLOPS. It was found that the algorithm had a lower level of complexity than MMSE. Furthermore, the robustness of the proposed algorithm was examined against a longer cyclic prefix, and the results proved a stable profile in terms of BER performance. For future work, the complex-valued DL has the potential to be explored further to improve its usefulness and significance in underwater communications.

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