Indian Journal of Pure & Applied Physics
Vol. 63, August 2025, pp. 741-749
DOI: 10.56042/ijpap.v63i8.20097

Implementation of an Empirical Acoustic Channel Model Using OFDM–DWT Technique

Kadali Lakshmi[a,b*], Ashraf Hossain[a] & Kavicharan Mummaneni[a]

[a]Department of ECE, National Institute of Technology, Silchar, Assam 788 010, India

[b]Department of ECE, Vignan's Institute of Information Technology, Visakhapatnam 530 049, India

Received: 27 May 2025; accepted: 8 July 2025

Several environmental factors, such as depth, salinity, frequency, and ambient noise, influence underwater acoustic communication (UAC). These factors reduce the integrity of signals, thereby decreasing system performance and increasing transmission errors. Out of these, noise is a major constraint that reduces communication reliability. To counter this, the current research suggests implementing a denoising technique using the discrete wavelet transform (DWT) combined with orthogonal frequency-division multiplexing (OFDM). Specifically, the DWT soft thresholding method is employed to reduce noise, while OFDM is used to reduce inter-symbol interference (ISI) and enhance spectral efficiency. OFDM combined with DWT is a significant contributor to reducing the bit error rate (BER), as demonstrated by a semi-analytic model used for calculating the BER. The modeled underwater channel impulse response (CIR) consists of 16 discrete taps. The taps have exhibited exponentially decreasing amplitudes between approximately 0.44 and 0.10, thereby modeling accurate energy dispersion and delay spread in shallow aquatic media. Simulation results confirm that the suggested methodology detects a BER of 10^{-7} at an SNR of 20 dB, with power efficiency measured by a peak-to-average power ratio (PAPR) of 8.5 dB, obtained using MATLAB simulations.

Keywords: Denoising, DWT, OFDM, Soft Thresholding, Underwater acoustic communication, PAPR

1 Introduction

Underwater communication reliability stands vital for defence operations, together with environmental monitoring and exploration duties as well as underwater robot control systems[1]. Underwater conditions create major constraints that affect how underwater communication systems should be developed and performed[2]. The main obstacle in underwater communications stems from high background noise, which originates from natural oceanic flows and sea creatures as well as human-made operations[3]. Maintaining signal integrity becomes possible only through successful noise reduction methods. Noise interference damages communication signals during underwater acoustic communications since it produces severe signal modulation that worsens both accuracy and quality levels[4]. The reliability of UAC systems depends on their ability to handle dual effects of multipath propagation alongside the three types of underwater signal distortions that include sea surface and bottom reflections and Doppler shift, and signal scattering losses[5-6]. The collection of sophisticated signal processing techniques helps both reduce noise disturbances for signal clarity and eliminate signal interference. Proper underwater acoustic channel modeling demands precise management of environmental factors that encompass water depth and salinity[7]. Various denoising techniques, such as wavelet thresholding, adaptive filtering, and deep-learning-based techniques, have been designed to reduce noise while preserving vital signal components, thus enabling effective data transmission[8]. Researchers have designed many denoising algorithms that are specifically aimed at addressing the unique characteristics of underwater acoustic noise, hence improving overall communication performance[9]. Denoising techniques are the cornerstone in mitigating the adverse effects of noise by filtering out unwanted signal components, thus enhancing the quality and reliability of transmitted data[10]. A commonly utilized method involves the integration of OFDM with denoising techniques, which has demonstrated efficacy in estimating underwater communication channels and enhancing UAC performance. Table 1 presents a comparative assessment of various denoising methodologies employed in UAC, underscoring their effectiveness in mitigating noise and augmenting signal quality.

*Corresponding author: E-mail:kadalilakshmi@gmail.com

Table 1 — Comparison among different denoising methods in underwater acoustic communication

Author	Methodology	Outcome	Challenges
Gorodon M Wenz[11]	The research integrates historical analysis, field data, and experiments to categorize noise types, assess acoustic signals using hydrophones, analyze variability with statistical methods, and explore noise dynamics under different environmental conditions.	The study advanced underwater noise understanding by identifying noise sources, environmental correlations, anthropogenic impacts, and bio-acoustic contributions, and informing predictive models for sonar and ecological assessments.	Lack of mid-ocean and under-ice data, high temporal variability, and limited integration of biological noise.
Y Lin *et al.*[12]	The paper utilizes the DWT with the Symlets sym5 wavelet for decomposing ECG signals, employs soft-thresholding to reduce noise, detects the QRS complex through adaptive windows and thresholding, and validates the algorithm using the MIT-BIH arrhythmia database.	The methodology achieves impressive results, boasting over 99.94% sensitivity for R peak detection, 99.75% for P waves, 99.7% for T waves, and notable improvements in Signal-to-Noise Ratio (SNR), surpassing other methods by at least 1 db.	The paper acknowledges challenges such as power-line interference and motion artifacts that complicate ECG analysis, and it highlights difficulties in applying the algorithm to real-time monitoring during physical activities, particularly at higher speeds.
Milica Stojanovic[13]	The paper models underwater acoustic propagation, addressing multipath and phase distortion, utilizes advanced signal processing like Doppler shift modeling and sparse channel estimation, and emphasizes experimental measurements to analyze acoustic channel statistics without standardized fading models.	The research highlights the impact of acoustic channel variability on signal reception, limits on communication capacity due to distance and noise, the need for adaptive modulation and MIMO techniques, and energy efficiency methods like increased bit rates to optimize underwater modem performance.	The research identifies challenges such as environmental variability, bandwidth limitations of acoustic transducers, and the complexity of channel models requiring resource-intensive experimental data for accuracy.
Daniele Borio *et al.*[14]	The paper presents a semi-analytic approach to evaluate the Receiver Operating Characteristic (ROC) under DVB-T interference, reducing computational load by leveraging system analytics instead of resource-intensive Monte Carlo simulations.	The study demonstrates the semi-analytic approach's efficiency in reducing complexity while ensuring accurate parameter estimation and performance evaluation, including jitter tracking.	The paper highlights challenges with modeling non-linear transmission effects under noise and varying GNSS receiver performance, emphasizing careful assumptions despite the precision of the semi-analytic approach.
Reza Barazideh *et al* .[15]	The paper presents a UWA communication system using OFDM and a memoryless analog nonlinear preprocessor (MANP) to reduce impulsive noise.	MANP effectively suppresses impulsive noise and improves BER and SNR compared to traditional methods such as blanking and clipping.	Implementation of MANP requires precise calibration to adapt to changing impulsive noise levels.
JMizeraczyk *et al.*[16]	This study proposes a reliable method for underwater wireless data transmission in hydroacoustic channels under non-line-of-sight (NLOS) conditions using multiple frequency-shift keying (MFSK) modulation.	The MFSK technique performed better regarding bit error rate than direct sequence spread spectrum (DSSS) and binary phase shift keying (BPSK) methods.	This study addresses the challenges in data transmission due to multipath propagation
S Mu *et al.*[17]	This study uses the T-MP (Threshold Matching Pursuit) algorithm for channel estimation.	The T-MP algorithm employs an adaptive threshold dynamically adjusted based on SNR to balance the accuracy.	Inter-carrier interference (ICI) due to the Doppler effect is a major challenge in estimating the channel in underwater acoustic (UWA) communication systems.
N Ansari *et al.*[18]	The real-time shallow water channel is estimated by 2-D frequency localization and compressive sensing with prior information.	Energy efficiency is improved and the channel is very accurate by using compressive sampling.	High complexity of the system.

X Feng *et al.* have developed temporal sparse Bayesian learning (TSBL) methods for channel estimation using OFDM by leveraging temporal correlation and sparsity to improve BER and mean square error (MSE) performance[19]. Jiasheng Guo*et al.* study is focused on establishing the paths for underwater acoustic orthogonal frequency division multiplexing (UWA-OFDM) systems in a new manner through a conditional Wasserstein generative adversarial network gradient penalty (CWGAN-GP). The authors have built the U-Net inspired by convolutional neural networks, and the research here seeks to perform channel estimation with improved mean performance squared error (MSE) and bit error rate (BER) performance. Both the CWGAN-GP and the U-Net CNN play crucial roles during the channel estimation procedure. Also, this research presents a method for estimating underwater channels, depending on the orthogonal frequency division multiplexing framework and discrete wavelet transform[20].

The design is acoustic-specific for communication in the oceanic environment. The main contributions of this current study are as follows

1. Analysis of OFDM for enhancing bandwidth efficiency, SNR, and BER.
2. Implementation of denoising algorithms to improve signal quality and reduce interference.
3. Implementation of a channel by OFDM-DWT to achieve effective communication in an underwater environment.

2 Optimized Wavelet-Based Dwt Thresholding for Noise Reduction and Signal Enhancement.

UAC is extremely difficult because of issues like ambient noise, multipath propagation, and Doppler effects. The DWT is an important signal processing tool for UAC that offers greater time-frequency resolution than traditional Fourier-based methods[21]. The effectiveness of DWT-baseddenoising depends on using proper wavelet functions and Thresholding methods[22]. This article optimized the signal using the DWT thresholding method with the Symlet(sym4) wavelet and tested for noise reduction and signal reconstruction quality.

2.1 The Denoising Wavelet Process

The elimination of noise is achieved by setting a threshold for the complex features that emerge from breaking down the signal by discrete wavelet transform (DWT). After this, the signal is put back together using the inverse DWT (IDWT). DWT has an impact on separating noise, which is why it's used. It breaks down the signal with wavelet basis functions ψ (t), which are defined as[23]

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{j}t - k) \quad \text{... (1)}$$

where j is the scale index, and k is the translation index.

The DWT is represented as

$$D_{j,k}[n] = \sum_{n=1}^{N} x[n].\psi_{j,k}[n] \quad \text{... (2)}$$

where$x[n]$ is the discrete input signal, $\psi_{j,k}[n]$ is the wavelet function

The wavelet denoisingprocess is performed by the following three steps, represented in Fig. 1.

1. Wavelet Decomposition
2. Wavelet Thresholding
3. Wavelet Reconstruction

2.1.1 Wavelet Decomposition

Wavelet decomposition transforms the received OFDM signal to a time-frequency representation, which is less vulnerable to channel distorting effects such as multipath fading and the Dopplereffect[24]. Compared to conventional sinusoidal basis functions, FFT-based OFDM, wavelet basis functions, and DWT based OFDM are more robust to Doppler shifts and multipath fading. Since wavelet basis functions offer higher time and frequency domain localization. During wavelet decomposition, the OFDM signal that has been transmitted undergoes multi-level sub-band decomposition, where it is divided into two groups of coefficients by consecutive filtering operations[25].

Approximation coefficients(A_k) maintain the low-frequency content of the signal, which has most of the structural information and energy. Most of the major subcarrier information is stored in the coefficients in OFDM-based DWT, represented in Eq 10.

Detail coefficients(D_k) are the elements of high-frequency noises due to rapid changes from multipath interference and ambient noise. The coefficients are important to improve the signal

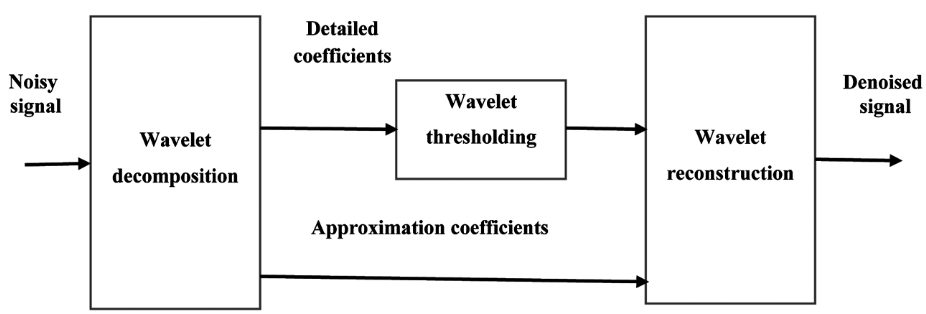

Fig. 1 — Representation of the wavelet denoising process

features, but are susceptible to acoustic noise underwater, as depicted in Eq11.

2.1.2 Wavelet Thresholding

Following decomposition, wavelet Thresholding is applied to the detail coefficients to reduce noise levels and optimize the signal-to-noise ratio SNR of the received OFDM signal[26].

Underwater acoustic communication channels are characterized by a range of noise sources such as ambient and impulsive noises, which primarily impact the higher-frequency components of the transmitted signal. Using an optimal threshold, usually determined by statistical methods such as universal Thresholding, noise-related coefficients can be reduced[27]. In particular, soft Thresholding (T)in Eq 3 is preferable to hard thresholding since it can reduce the noise progressively without creating sudden changes, thereby maintaining the fidelity of the underlying signal[28]. This process effectively removes the impact of noise while maintaining key signal features that are critical to correct demodulation and decoding.

$$T = \sigma\sqrt{2\log N} \quad \text{... (3)}$$

where T is the threshold value used in wavelet denoising or signal processing to suppress noise. σ is an estimate of the noise standard deviation, calculated as

$$\sigma = \frac{median(|d_i|}{0.6745}$$

d_i is wavelet detail coefficient at position i and constant 0.6745 normalized the median absolute deviation (MAD)under assumption of Gaussian white noise. N is the total number of wavelet coefficients in the signal.

2.1.3 Wavelet Reconstruction

The inverse discrete wavelet transform (IDWT) is then used to reconstruct the time-domain OFDM signal from the thresholded wavelet coefficients[29]. Reconstruction is done by combining the thresholded approximation and detail coefficients to restore the original signal with reduced noise and minimal distortion. In DWT-based OFDM systems, wavelet reconstruction plays a key role in maintaining subcarrier orthogonality and spectral efficiency[30]. By effective reconstruction of the denoised signal, this process helps to minimize the BER and enhance overall communication efficiency, which is particularly beneficial in the complex and dynamic environment of underwater acoustic channels.

3 System Framework

UAC Empirical models are developed to understand the dynamic behavior of underwater channels to some extent, which are not exactly suited for real-world environments. The proposed and developed model, with a combination of existing models with new advanced techniques, provides a view of better estimation of the channels in a simulated environment using MATLAB software by considering the underwater parametersas a mimic behavior of the real-world environment.

3.1 OFDM based DWT UAC System

In conventional OFDM systems, subcarriers are produced by the FFT. Wavelet-based OFDM employing the DWT provides greater time-frequency localization and greater immunity against interference and noise[31]. The proposed framework applies Symlet (Sym4) wavelets for OFDM modulation and demodulation, and adaptive soft thresholding in the wavelet domain for cancellation of noise before reconstructing the original signal by the IDWT[32].The entire communication process is schematically illustratedin Fig. 2.

3.1.1 Transmitter Structure Realization

In the transmitter, the binary data stream is 256-QAM modulated, essentially mapping multiple

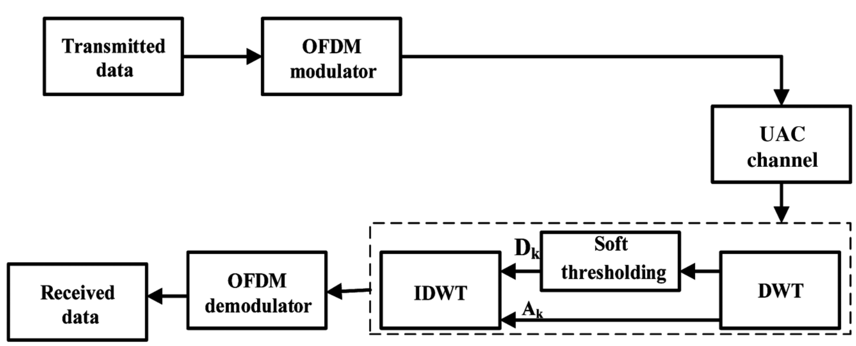

Fig. 2 — Block diagram of OFDM based DWTUAC system

bits to a symbol to maximize spectral usage, critical in bandwidth-limited underwater channels. The modulated data is paralleled for OFDM conversion, which resists propagation delay and multipath effects by spreading data over orthogonal subcarriers, precluding interference. An IFFT converts the signal to the time domain for transmission[33].The input binary sequence (b) is represented as

$$\mathrm{b} = [\mathrm{b}_0, \mathrm{b}_1, \ldots, \mathrm{b}_\mathrm{N}] \quad \ldots (4)$$

where $b_i \in \{0,1\}$ represents each bit in the input stream. These bits are grouped into symbols and mapped to a complex constellation using QAM

$$s_k = M(b_k) \quad \ldots (5)$$

where $M(.)$represents the modulation mapping function.

The modulated OFDM signal x(n) in the time domain is then given by

$$\mathrm{x(n)} = \sum_{\mathrm{k}=0}^{\mathrm{N}-1} \mathrm{X_K} \mathrm{e}^{\frac{\mathrm{j}2\pi\mathrm{kn}}{\mathrm{N}}} \quad \ldots (6)$$

3.1.2 Marine Acoustic Communication Medium

Underwater sound channels face several problems, including echoes, frequency changes, and extra noise. Echoes happen when signals bounce off the water's surface, the ocean floor, and things underwater causing many delayed copies of the sent signal to reach the receiver[34]. Also, the Doppler effect which occurs when the sender and receiver are moving relative to each other shifts frequencies and can mess up signal consistency. What's more, both natural background noise and human-made interference make communication harder[35]. The channel impulse response can be modeled as

$$h(t) = \sum_{l=1}^{L} \alpha_l \, e^{-j2\pi f_d t} \delta(t - \tau_l) \quad \ldots (7)$$

where α_l is represents the attenuation of the l^{th}multipath component,τ_l = Delay associated with the l^{th} path,$f_d$is the Doppler shift due to relative motion,$\delta(t)$ = the Dirac delta function.

The noise in the UAC channel is affected by several environmental factors, including water turbulence, shipping traffic, and thermal noise. The PSD$S_n(f)$ of the noise can be approximated as follows

$$S_n(f) = N_w(f) + N_t(f) + N_s(f) + N_m(f) \quad \ldots (8)$$

where $N_w(f)$ is turbulence noise, $N_t(f)$ is the thermal noise, $N_s(f)$ is the shipping noise and $N_m(f)$ is the man-made noise.

3.1.3 Wavelet Based Receiver Design: DWT and IDWT Implementation

At the receiver, the incoming signal is initially filtered using the DWT to remove noise added by the underwater acoustic channel[35]. The incoming signal is split into the approximation coefficients (low-frequency) and the detail coefficients (high-frequency) at various levels of resolution.

The received signal $y(t)$can be expressed as

$$y(t) = \sum_{l=1}^{L} \alpha_l \, e^{-j2\pi f_d t} x(t - \tau_l) + n(t) \quad \ldots (9)$$

where $x(t)$ is the transmitted signal and $n(t)$ represents additive noise.

The decomposition process consists of approximation coefficients $A_k[n]$ and detail coefficients $D_k[n]$ which are mathematically represented as

$$A_k[n] = \sum_m h[m - 2n] X[m] \quad \ldots (10)$$

$$D_k[n] = \sum_m g[m - 2n] X[m] \quad \ldots (11)$$

where $A_k[n]$are the approximation coefficients, $D_k[n]$ are the detail coefficients, $h[n]$ is the low-pass filter, $g[n]$ is the high-pass filter, $X[m]$ is the received signal, m *and* n are the indices for signal decomposition.

To reduce noise, Soft Thresholding is applied to the detail coefficients, which can be expressed as

$$T_s(D_k[n]) = sgn(D_k[n]. \max(|D_k[n] - |\lambda, 0) \ldots (12)$$

where λ is the threshold level that determines noise suppression.

The noise-removed signal is reconstructed using the IDWT, combining the processed approximation and threshold detail coefficients.

$$X'[m] = \sum_n h'[m - 2n] A_k[n] + g'[m - 2n] T_s(D_k[n]) \quad \ldots (13)$$

where h' and g' are the synthesis filters corresponding to the inverse wavelet transform.

The reconstructed denoised signal can be obtained at the receiver side with enhanced signal quality and a low BER value.

4 Results and Discussion

The simulation model, incorporating the proposed techniques, estimates the UWC conditions using MATLAB software. The resulting data provide valuable insights, including noise reduction achieved by adjusting filter coefficients based on channel conditions, as well as improvements in SNR and BER in dynamic underwater environments. Table 2 presents the list of simulation parameters.

Figure 3 indicates the verification of the OFDM-DWT denoising technique in the time domain. The original signal in subplot 1 is specified as a sine wave of amplitude 1V. Upon transmission through a simulated underwater channel with noise (subplot 2), the peak amplitude of the signal rises to approximately 2V, which verifies the existence of noise and signal distortion. Upon application of DWT-based denoising, the reconstructed approximation at level 4 (subplot 3) effectively restores the sine wave to its original amplitude of 1V, which is an indication of effective noise removal. The reconstructed detail coefficients at levels 4 (subplot 4) and 1 (subplot 5) remain in low amplitude ranges (<0.2V and <0.1V, respectively), thereby serving as proof that the noise energy predominantly exists in the high-frequency components D1 and D2. Figure 4 shows the multilevel

Table 2 — UAC based simulation parameters

Parameters	Value
Modulation order(M)	256 QAM
Cyclic prefix(CP)	32
Frequency(f)	10KHz to 20KHz
Bandwidth	10KHz
Number of subcarriers	64
FFT or IFFT size	256
Temperature(T)	25℃
Salinity(s)	35 ppt
Depth(D)	40 m to 100 m
Distance(d)	1 km to 10 km

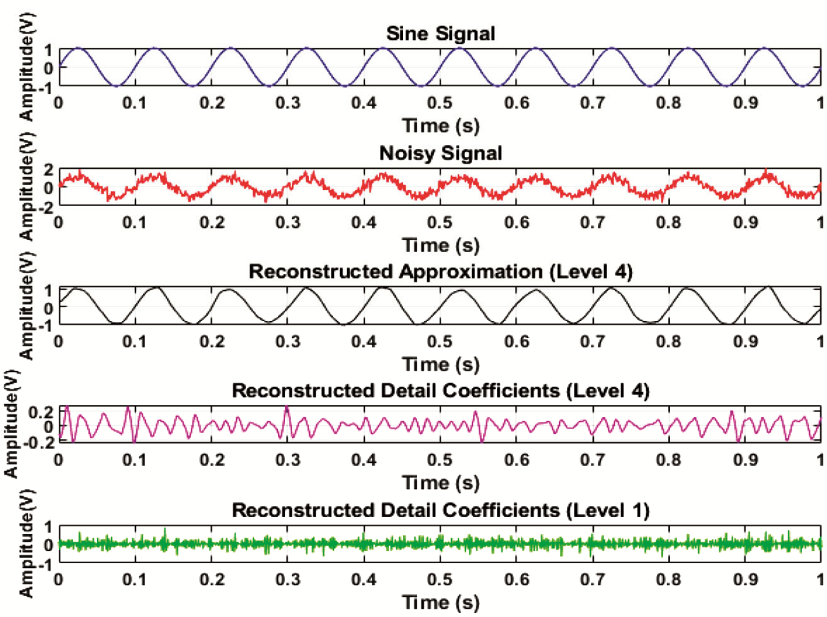

Fig. 3 — Symlet (sym4) wavelet decomposition of a noisy sine wave showing approximation (Level 4) and detail coefficients (Level 1& Level 4)

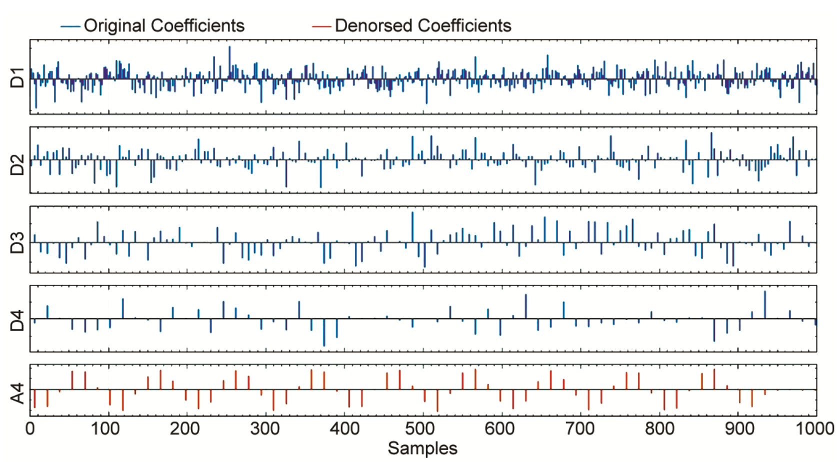

Fig. 4 — Multilevel wavelet decomposition (Level 4) of received underwater acoustic signal using Symlet (sym4) in OFDM-DWT framework

decomposition of the noisy input signal into a single approximation coefficient (A4) and four detail coefficients (D1–D4) using DWT.

The D1 component shows prominent high-frequency noise with amplitude values dispersed roughly around -0.3 to +0.3, indicating high levels of noise content. With an increase in decomposition level, the detail coefficients (D2–D4) become increasingly sparse and less energetic, with amplitude values spread roughly around ±0.1, indicating a lesser effect of noise at lower frequency bands. The approximation part A4 has well-defined periodic structures with amplitude values dispersed roughly around -0.2 and +0.2, indicating high correlation with the original content of the signal. Figure 5 represents the Channel Impulse Response (CIR) of the underwater acoustic channel, capturing the multipath propagation effects introduced by reflections from the sea surface, seabed, and underwater obstacles**.** The CIR extends over 35 time samples**,** with normalized amplitude values reaching up to 0.4. The presence of multiple delayed signal components confirms the impact of multipath interference, which leads to ISI**.**

The dominant peaks in the response indicate that certain propagation paths contribute more strongly to the received signal, while weaker multipath components introduce fading and distortion. The dispersive nature of CIR highlights the necessity for wavelet-based equalization techniques, which can mitigate ISI by reconstructing the signal using adaptive thresholding and noise suppression.

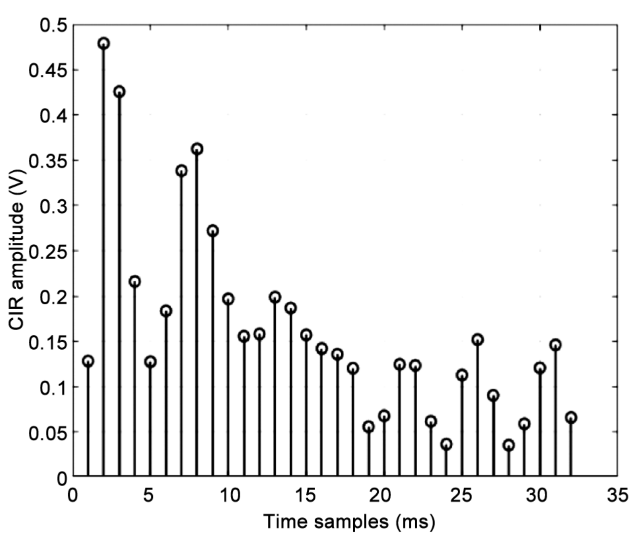

Fig. 5 — Channel Impulse Response of a DWT-enhanced OFDM system in the UAC system

Figure 6 depicts the BER performance trend as a function of SNR for an underwater acoustic communication system based on conventional OFDM with FFT-based modulation and demodulation, without wavelet-based denoising, as shown in the plot. In low SNR conditions (0–10 dB), the system exhibits large BER values, from 0.5 to 0.2, due to multipath fading and underwater environment noise. With rising SNR, the BER continues to decrease step by step, reaching 0.01 at approximately 25 dB and 0.001 at approximately 30 dB. This indicates that while FFT based OFDM successfully eliminates inter-symbol interference, it lacks the noise-reducing capability of wavelet-assisted methods.

Figure7 represents the SNR before and after denoising of the system using DWT technique at the

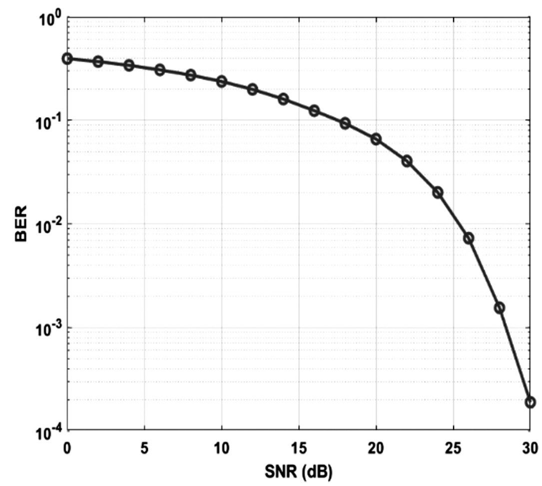

Fig. 6 — BER Performance of FFT based UAC-OFDM system over multipath channel

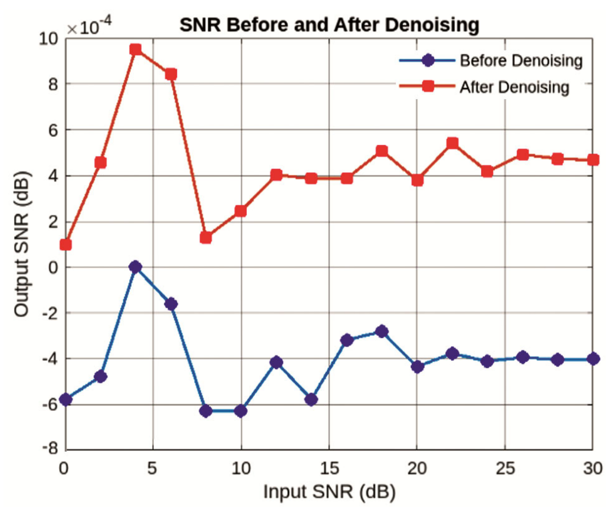

Fig. 7 — Enhanced SNR of system model: Output SNR versus Input SNR

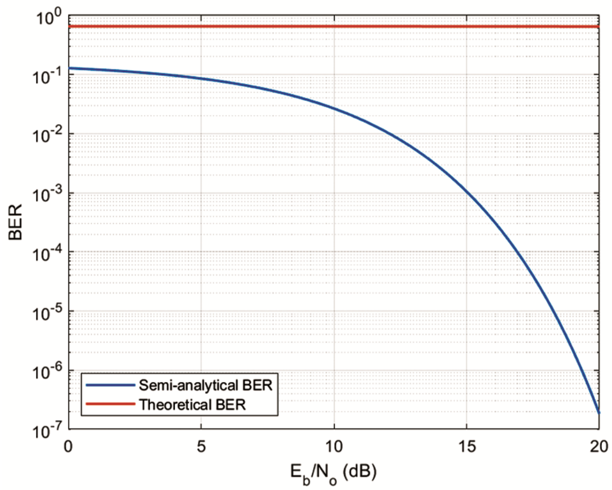

Fig. 8 — Analysis of BER versus SNR using the Semi-analytic approach

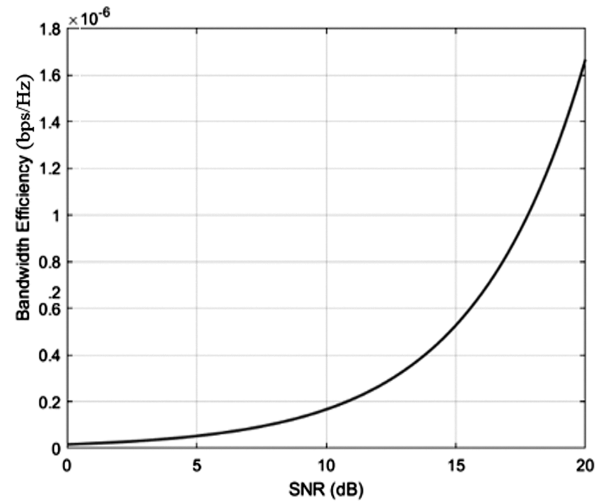

Fig. 9 — Exponential growth of bandwidth efficiency versus SNR for DWT-UWAC

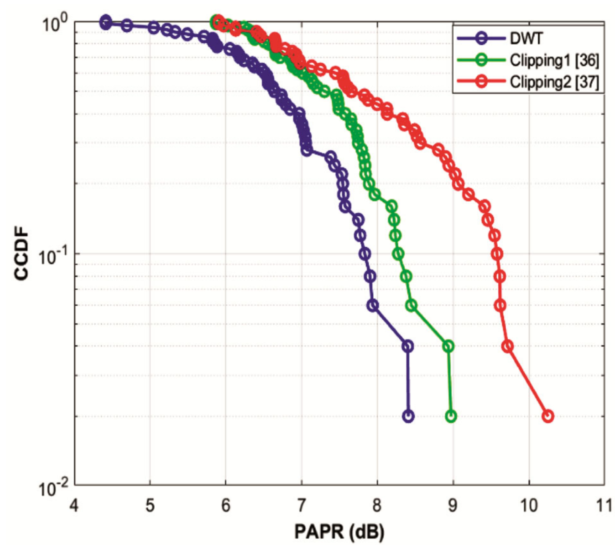

Fig. 10 — Performance analysis of PAPR reduction techniques using clipping and OFDM–DWT methods

receiver and shows that SNR values are changed due the abundant nature of the underwater environment. The SNR value is -0.0006 and it changes after application of DWT SNR value of 0.001.Figure 8 presents the theoretical BER values along with the application of a semi-analytic approach for a clearer visualization of the bit errors present. As the energy per bit to noise ratio increases, a rapid decreasein bit errors is observed, demonstrating a dependent relationship between the BER and SNR.

Figure 9 illustrates the bandwidth efficiency of a UWAC as a function of the SNR in decibels (dB), showing a positive, nonlinear relationship.

The SNR ranges from 0 to 20 dB, while the bandwidth efficiency is measured in a scaled unit, with values on the order of 0.5bps/Hz. As the SNR increases, the bandwidth efficiency rises exponentially, indicating that improved signal quality enhances system performance. As it is evident from Fig. 10. The DWT-based system has a PAPR of approximately 8.5 dB with a Complementary cumulative distribution function(CCDF) of 0.01, better than Clipping1[36] and Clipping2[37] schemes, having 9 dB and 10.2 dB, respectively.

This tremendous PAPR reduction makes the DWT-based OFDM significantly more appropriate for application in underwater channels where energy efficiency and quality of the signal are of utmost importance, given bandwidth limitations and multipath propagation. The conclusion is sure to verify that adding DWT to OFDM systems improves system robustness and energy efficiency for underwater acoustic channels.

5 Conclusion

This study presents an effective de-noising algorithm for underwater acoustic communication that combines the discrete wavelet transform with soft thresholding and OFDM techniques. By calculating BER using a semi-analytic approach tailored to UWAC characteristics. This improvement translates into greater communication reliability, better signal integrity, and the potential for higher data transmission rates, making the proposed approach highly effective for communication.The OFDM communication system is prone to a high PAPR, which can lead to inefficiencies and increased power consumption, particularly in resource-constrained underwater acoustic communication systems. This issue becomes more significant in underwater environments, where power resources are limited, and efficient communication is crucial. To address this challenge, dynamic voltage frequency scaling (DVFS) can be employed as an effective technique to reduce power consumption. DVFS dynamically adjusts the voltage and frequency levels of the system based on the communication load, thus mitigating the high PAPR problem.

References

1 MohsanS A H,SadiqY, Li M, LiangJ & Khan M A, *J Mar Sci Eng*, 11 (1) (2023) 124.
2 Domingos F P F, LotfiA, IhianleI K, Kaiwartya O & Machado P, *Electron (Basel)*, 14 (1) (2024) 7.
3 AliM F, Jayakody D N K, ChursinY A, Affes S & Dmitry S, *Arch Comput Methods Eng*, 27 (5) (2020) 1379.
4 Rahmati M & PompiliD, *IEEE J Ocean Eng*, 43 (3) (2018) 777.
5 Oliveira T C A, Lin Y-T & Porter M B, *Front Mar Sci*, 8 (2021) 1.
6 Erbe C, Duncan A & Vigness-Raposa K J, Exploring animal behaviour through sound, *Springer* 1 (2022) 185.
7 Yang H, Shi W-S & LiG-H, *Def Technol*, 28 (2023) 87.
8 Zhang Y, Yang Z, Du X & Luo X, *J Mar Sci Appl*, 23 (1) (2024) 222.
9 Wang J*et al.*, *IEEE Trans Veh Technol*, 70 (1)(2021) 429.
10 Song Y, Liu F & Shen T, *IEEE Access*, 12 (2024) 81483.
11 Wenz G M, *J Acoust Soc Am*, 51 (3) (1972) 1010.
12 Lin H-Y, Liang S-Y, Ho Y-L, Lin Y-H, & Ma H-P, *IRBM*, 35 (6) (2014) 351.
13 Stojanovic M & Preisig J, *IEEE Commun Mag*, 47 (1) (2009) 84.
14 Borio D & Cano E, *MATLAB A Fundamental Tool Sci Computing Eng Appl,* 2 (2012) 286.
15 Barazideh R, Sun W, Natarajan B, Nikitin A V &Wang Z, *IEEE 9th Annual Computing Commun Workshop and Conf (CCWC)*, 2019.
16 Mizeraczyk J, Studanski R, Zak A & Czapiewska A, *Sensors (Basel)*, 21 (23) (2021) 7825.
17 Mu S, Gao W, Li Y, Jiang L, Pan M & Xu H, *IEEE Access*, 11 (2023) 109131.
18 Ansari N, Gupta A S & Gupta A, *J Acoust Soc Am*, 145 (5) (2019) 2955.
19 Feng X, Wang J, Sun H, Qi J, Qasem Z A H & Cui Y, *Signal Proces*, 207 (2023) 108951.
20 Guo J, Guo T, Li M, Wu T & Lin H, *Electronics (Basel)*, 13 (4) (2024) 689.
21 Wang B, Si Q & Jin M, *IEEE Commun Lett*, 24 (6) (2020) 1271.
22 Veeraiyan V B, Denoising methods for underwater acoustic signal, in *Advances in Underwater Acoustics*, InTech, 2017.
23 Song P, Tan Y, Geng X & Zhao T, *IEEE Access*, 8 (2020) 131626.
24 Saad W, El-Fishawy N, EL-Rabaie S & Shokair M, *Advances in Grid and Pervasive Computing* (2010) 533.
25 Ayeswarya R & Prabha N A, *IETE J Res*, 68 (1) (2022) 732.
26 Bouhlel A, Sakly A & Ikki S S, *Future Trends in 5G and 6G*, Boca Raton CRC Press, (2021) 235.
27 Kar S C, Hussain S & Fernando X, *IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2014.
28 Khan A & Shin S Y, *IETE Technol Rev,* 35 (1) (2018) 17.
29 Dilmaghani R & Ghavami M, *IET Commun*, 2 (2) (2008) 353.
30 Bauer M, Anselment R, & Dostert K, *IEEE International Symposium on Power Line Communications and Its Applications*, 2009.
31 Pinjare S L, Cyril P P & Chetan N J, Underwater OFDM Model Using DWT And FFT Methods, Open Science Framework, 25-Jul-2023.
32 Zhang Y, Chang J, Liu Y, Shen X & Bai W, *IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, 2022.
33 Proakis J G, Sozer E M, Rice J A & Stojanovic M, *IEEE Commun Mag*, 39 (11) (2001) 114.
34 Chitre M, Shahabudeen S & Stojanovic M, *Mar Technol Soc J*, 42 (1) (2008) 103.
35 Gao R, Liang M, Dong H, Luo X & Suganthan P N, Underwater acoustic signal denoising algorithms: A survey of the state-of-the-art, *IEEE Trans Instrum Meas,* 2025, 1.
36 Yang L, Bi Z, Liang X, Zhao L, Zhang J & Peng J, *IEEE Photonics J*, 16 (5) (2024) 1.
37 Xing S, Qiao G & Ma L, *IEEE Access*, 6 (2018) 24128.