Ocean Systems Engineering, *Vol. 15, No. 3 (2025) 271-295*
https://doi.org/10.12989/ose.2025.15.3.271

Hybrid FEDformer-LSTM model for enhanced heave displacement prediction in offshore buoys

N. Santhosh*[1], S.M. Vinu Kumar[2], R. Sundar[3],
V. Vadivelvivek[4] and C. Dineshbabu[5]

[1]Department of Mechanical Engineering, Easwari Engineering College, Chennai, India
[2]Department of Mechanical Engineering, Sri Krishna College of Technology, Coimbatore, India
[3]Scientist – E, Ocean Observation Systems, National Institute of Ocean Technology, Chennai, India
[4]Department of Mechanical Engineering, Bannari Amman Institute of Technology, Sathyamangalam, India
[5]Department of Mechanical Engineering, Kongunadu College of Engineering and Technology, Trichy, India

(Received June 1, 2025, Revised August 22, 2025, Accepted August 28, 2025)

Abstract. Buoys are a crucial structure used offshore, and the data acquired from them is essential for marine navigation, offshore engineering, coastal management, weather forecasting and wave energy research. To optimize wave energy extraction and guarantee the dependability of ocean-based structures, accurate heave displacement forecasting is essential. In order to enhance the estimation of heave displacement, a unique hybrid model that combines a Long Short-Term Memory (LSTM) network with the Frequency Enhanced Decomposition Transformer (FEDformer) is implemented. The proposed FEDformer – LSTM hybrid model competently captures long-range dependencies and non-linear temporal patterns in wave data by employing the frequency-domain decomposition powers of FEDformer and the temporal learning advantages of LSTM. Experimental data are retrieved from the buoy data of the National Institute of Ocean Technology (NIOT), which includes wave height, wind speed, and other data from key maritime areas. The hybrid model beats state-of-the-art forcasting algorithms and independent deep-learning techniques in terms of correlation metrics, Mean Absolute Error (MAE) and Root Meam Square Error (RMSE), affording to proportional tests carried out using real-world buoy datasets. The findings indicate that the FEDformer-LSTM model is more appropriate prediction model for the proposed application.

Keywords: deep learning; FEDformer; ocean-based structures; wave energy conversion

1. Introduction

Wave energy plays a vital role in renewable energy source among the various renewable energy resources available in the world. The wave energy is harvested by devices such as wave energy converters (WECs) and the point absorber is one of the predominant wave energy harvesting devices attracted the attention of researchers and engineers. These devices generate power by using the buoys vertical (heave) motion, which is caused by ocean waves. Apart from energy extraction, the wave floating buoys and other offshore structures are essential for marine operations, renewable energy gathering and oceanographic monitoring. For such systems to be

---

*Corresponding author, Assistant Professor, E-mail: santhoshmech10@gmail.com

http://www.techno-press.org/?journal=ose&subpage=7 ISSN: 2093-6702 (Print), 2093-677X (Online)

stable, controllable, and reliable, heave displacement that is the vertical motion caused by ocean waves must be accurately predicted. However, precise heave displacement forecasting is challenging due to the inherent variability in wave patterns and the complex and nonlinear dynamics of ocean settings. Exact forecasting heave displacement is still a chronic difficulty, even with major advances in wave energy research. Traditional methods mainly depend on frequency domain response amplitude operators (RAOs) and linear wave theory, which assume Gaussian and stationary sea states. It is intricate to capture the stationary and nonlinear behaviours of actual ocean waves by implementing these models, particularly in shallow water or in rough weather conditions (Shi *et al.* 2016). Traditional methods such as frequency-domain models and Response Amplitude Operators (RAOs), normally assume linearity in sea states. However, these assumptions are undervalued in real-world scenarios, especially during nonlinear and abrupt wave conditions. A research highlights the challenges encountered during the prediction of vessel motions using RAOs due to the intricate nature of ocean waves (Cademartori *et al*. 2023). Artificial Neural Networks (ANNs) and LSTM network are two unique examples of machine learning and deep learning models that have been examined to overcome these limitations. Although these models are capable of predicting sequential relationship in wave data, they commonly have issues in handling long range dependencies and show suboptimal performance when handling with noisy or sparse datasets (Xiao and Lu 2024). To improve performance, LSTM and other deep network have also been integrated with signal decomposition methods such as Wavelet Transform (WT) and Empirical Mode Decomposition (EMD). Nevertheless, these integrated models still have complexities in simulating the complex frequency components of ocean wave spectra and simplifying across various marine habitats (Chen *et al.* 2013). LSTM networks have been implemented to forecast wave energy and heave motions. While they can capture temporal dependencies, LSTMs may face difficulty with long-range dependencies and noisy or sparse datasets. An enhanced LSTM model was proposed to address some of these issues, but accuracy remains a challenge in forecasting under varying sea conditions (Tang *et al*. 2021). Combining LSTM with signal decomposition techniques like Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) has been tested to enhance forecasting accuracy. However, these hybrid models can be sensitive to noise and may not efficiently generalize across different marine environments. A study comparing various hybrid models and found that some improvements were noted, but still significant limitations existed in finding the complex frequency components of ocean wave spectra (Ospina and Valencia 2019). Many deep learning models focus primarily on time-domain features, potentially overlooking critical frequency-domain information essential for accurate wave pattern description. A novel machine learning architecture called, FreMixer, was proposed to address this gap by leveraging frequency-domain information, demonstrating improved performance in short-term wave forecasting (Zhou and Wang 2024). Furthermore, the majority of deep learning models now in use ignore important frequency domain information that is essential for describing wave patterns in favour of concentrating mostly on time-domain properties. As a result, they are less accurate over longer forecasting horizons and during abrupt sea state changes (Zhou *et al*. 2022). These studies together emphasize the requirement for more robust and adaptive models that can efficiently handle the nonlinear, non-stationary, and complex nature of ocean wave dynamics to enhance heave displacement forecasting in WECs. This proposed research work makes several key contributions to the field of wave energy forecasting and ocean-based structural monitoring through the development and implementation of a novel FEDformer–LSTM hybrid model. The FEDformer–LSTM model synergistically integrates the frequency-domain decomposition capabilities of the FEDformer with the temporal sequence learning strengths of LSTM. While LSTM networks are effective for learning temporal dependencies, they are often challenged by long-range dependencies and noise (Gao *et al.* 2024, Jailani *et al.* 2023). The FEDformer (Hou *et al.* 2025) enhances performance by capturing meaningful periodic patterns from frequency-domain representations, thus complementing the temporal learning of LSTM and enabling better generalization across dynamic sea states. Traditional models like RAOs and purely time-domain deep learning models assume linear and stationary wave behaviours, which limit their applicability in complex marine conditions. The hybrid approach influences the frequency-aware decomposition of FEDformer, addressing limitations of methods such as EMD and WT, which are sensitive to noise and inconsistent across environments. This allows the model to robustly recognize the complex, nonlinear, and non-stationary characteristics of ocean wave spectra. Comparative evaluation using real-world buoy datasets from the NIOT proves that the proposed hybrid model significantly outperforms both standalone deep learning methods (e.g., LSTM, ANN) and hybrid decomposition models in terms of MAE, RMSE, and correlation coefficients. This highlights its practical utility for real-time control and decision-making in WECs and ocean monitoring systems. The study validates the proposed model using extensive buoy data from key maritime zones collected by NIOT, which includes wave height, wind speed, and other dynamic parameters. This real-world application confirms the operational viability of the FEDformer–LSTM framework in diverse and unpredictable ocean environments.

2. Related work

Ocean wave forecasting has been conventionally depends on physical and statistical models. The spectral wave model (SWAN) (Booij *et al.* 1999) and WaveWatch III (Tolman 2009, Ban *et al.* 2023, Elbisy 2015) are unique samples of physics-based models that solve wave action balance equations using boundary conditions and wind inputs. While effective over large domains, these models are computationally intensive and depend heavily on accurate meteorological inputs, limiting their real-time applicability (Zhang *et al.* 2024, Hanifi *et al.* 2023). To address these challenges, data-driven approaches have gained the attraction. Statistical models such as autoregressive (AR) and autoregressive integrated moving average (ARIMA) models have been used for wave height and period prediction (Vaswani *et al.* 2017). However, their performance decreases in complicated marine environments due to assumptions of linearity and stationarity. Recent advancements in machine learning (ML) have introduced non-linear, data-driven alternatives. Support Vector Machines (SVMs) and Gaussian Processes (GPs) have shown potential for short-term wave forecasting by learning from historical data without obvious physical modelling (Lim *et al.* 2021). Yet, these models often face difficulties in robustness when applied to noisy datasets or variable environmental conditions. Deep learning methods, particularly Recurrent Neural Networks (RNNs) and LSTM networks, have arisen as powerful tools to capture temporal dependencies in wave data (Wu *et al.* 2021). These models outperform traditional ML methods in modelling sequential ocean wave patterns but still suffer from limitations such as difficulty modelling long sequences and sensitivity to input noise. To overcome this, hybrid architectures have been proposed, integrating LSTM with signal processing techniques like Wavelet Packet Decomposition (WPD) and Variational Mode Decomposition (VMD) (Nie *et al.* 2023). These approaches improve signal clarity and enhance prediction accuracy. However, they often fail to generalize well across different marine locations due to overfitting or sensitivity to hyperparameters. Thus, the requirement remains for robust, adaptive, and generalizable models that can precisely predict the highly dynamic and non-linear nature of ocean waves across varied environmental conditions. Transformer-based architectures, formerly developed for natural language processing (Hochreiter *et al.* 1997), have recently gained significant attention in the field of time-series forecasting due to their superior ability to model long-range dependencies. Unlike recurrent models such as RNNs or LSTMs that depend on sequential processing, transformers use self-attention mechanisms to weigh the relevance of each time step across the entire sequence, allowing parallel computation and more effective learning of global patterns. One of the original works in this area is the Temporal Fusion Transformer (TFT) (Wen *et al.* 2022) which integrates attention with interpretable temporal dynamics, enabling multivariate forecasting with dynamic features. It confirmed considerable improvements over traditional LSTM-based models, predominantly in scenarios involving complicated temporal relationships and covariates. Following this, the Informer model (Hou *et al.* 2025) was introduced, tailored specifically for long-sequence forecasting. It reduced computational costs using a ProbSparse self-attention mechanism and a generative decoder. Informer's capability to handle very long input sequences with high forecasting accuracy has made it a strong candidate for environmental time-series applications, including meteorological and wave data. Further enhancement led to the development of the FEDformer (Frequency Enhanced Decomposition Transformer), which combines frequency-domain decomposition with a transformer-based backbone. FEDformer addresses two key boundaries in time-series forecasting: loss of long-term dependencies and poor frequency resolution. By implementing Fourier transform-based decomposition, FEDformer holds meaningful periodic and seasonal components while preserving temporal coherence. This makes it particularly effective for forecasting tasks involving oscillatory signals, such as ocean wave spectra and heave motion patterns in marine environments. Other transformer variants like Autoformer (Bengio *et al.* 1994) and PatchTST (Gers *et al.* 2000) have further enhanced the performance of transformers in time-series tasks by incorporating trend-seasonal decomposition and patch-based learning, respectively. These models validate the growing consensus that integrating frequency-aware processing with attention mechanisms yields more accurate and generalizable forecasting models. Collectively, transformer-based models have revolutionized time-series forecasting by enabling effective modelling of both short and long-term dependencies, robustness to input noise, and scalability to large datasets qualities critical for marine and environmental applications where data are often nonlinear, non-stationary, and multivariate. The combination of FEDformer and LSTM networks is intentionally motivated by the complementary power of both architectures in handling ocean wave time-series data, particularly for heave displacement forecasting. Ocean wave data are fundamentally nonlinear, non-stationary, and exhibit multiscale temporal dependencies, which challenge traditional and even standalone deep learning models. LSTM networks have been widely implemented to sequential forecasting problems due to their capability to capture short and mid-range temporal dependencies and mitigate vanishing gradient issues common in standard RNNs (Graves 2013). In marine environments, LSTM models have been implemented to forecast wave energy and motion, showing significant enhancement over conventional statistical models. However, they tend to struggle with learning long-range dependencies and are sensitive to input noise and data sparsity, which are common in buoy-collected datasets. On the other hand, FEDformer improves long-term forecasting performance by shifting part of the learning to the frequency domain. It decomposes time-series data using Fourier transforms to isolate low and high frequency components, allowing the model to identify periodic structures and seasonality more effectively (Zhou *et al.* 2022).

Unlike earlier decomposition methods such as EMD or WT, which often suffer from mode mixing and are sensitive to noise, FEDformer provides a more stable and interpretable frequency-aware representation. While FEDformer is highly effective in extracting global periodic patterns, it may underperform in capturing localized transient behaviors, especially when the signal is influenced by abrupt environmental changes or non-periodic noise. This is where LSTM complements the architecture. LSTM’s time-domain recurrence mechanism excels at learning localized, dynamic patterns and fine-grained temporal transitions that may not manifest in the frequency domain. By integrating FEDformer with LSTM, the hybrid model leverages the strength of frequency-domain decomposition in modelling periodic and trend-based components while simultaneously benefiting from LSTM’s ability to refine short-term, local predictions. This synergy allows the combined model to capture both global and local patterns, improve robustness against noise, and generalize better across diverse marine conditions (Makridakis *et al*. 2008). This combination is particularly relevant for real-time forecasting scenarios in wave energy conversion systems and offshore structural monitoring, where both short-term dynamics and long-range periodicity significantly impact system control and performance.

3. Methodology

3.1 FEDformer overview

The FEDformer utilizes the advantages of Transformer-based architecture integrated with frequency domain analysis in time-series forecasting. Considering the limitations in traditional forecasting models, FEDformer employs a dual-module architecture comprising the Frequency Enhanced Block (FEB) integrated with the Seasonal-Trend Decomposition Module (STL). At the core of FEDformer presents the frequency decomposition approach, which differentiates it from conventional transformer models. The core architecture consists of two main modules:

3.1.1 Frequency Enhanced Block (FEB):

The FEB implements a Fourier transform to convert the time series into a frequency domain. This conversion allows the model to identify global frequency components and select significant ones through a learnable frequency choice mechanism. By highlighting key frequency signals, FEDformer identifies periodic patterns and long-range dependences more efficiently.

3.1.2 Seasonal-trend decomposition using STL

STL decomposition splits the input time series into seasonal and trend components. These components are treated autonomously to enhance model interpretability and allow more precise depictions of dynamic patterns in data. The use of STL allows FEDformer to segregate and process repeating seasonal behaviours distinctly from underlying trends, significantly improving its predictive power.

Combined, these modules allow FEDformer to achieve enhanced performance by leveraging both the time and frequency domains, unlike conventional models that primarily depend on temporal attention mechanisms (Hou *et al.* 2025). Further, the FEDformer offers distinct advantages, such as effective long-term forecasting, where it reduces computational complexity which leads to improved long-range predictions. The model has the capability to naturally filter out high-frequency noise, which is irrelevant to forecasting tasks, which leads to cleaner input and

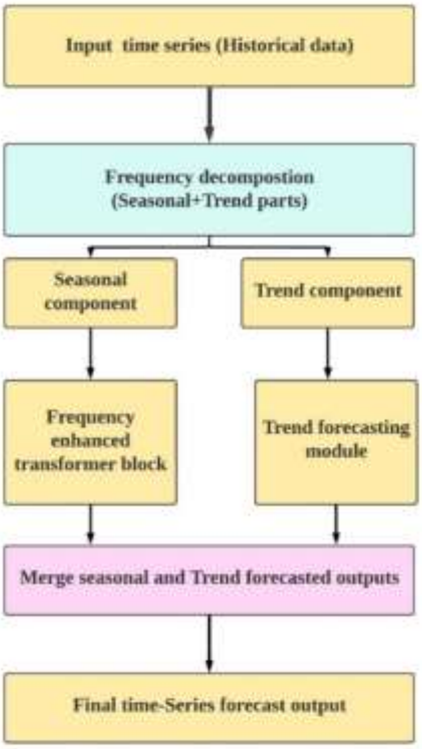

Fig. 1 Process Flow of FEDformer model

robust outputs. The model generalizes the diverse time-series dataset when it extracts the patterns in frequency domain even when the data with irregular and nonstationary inputs. FEDformer offers better interpretability, a feature mostly beneficial for applications in finance, energy, and climate where understanding model rationale is more complex. Hence, the FEDformer is predominantly appropriate for complex forecasting tasks, outpacing existing models like Autoformer and Informer in multiple benchmark datasets (Hou *et al.* 2025). The process flow of the FEDformer model is shown in Fig. 1.

3.2 LSTM overview

LSTM networks are a modified version of recurrent neural networks (RNNs) which is particularly developed for forecasting long-range time-based sequential data. Traditional RNNs deteriorate their capability to learn long-term patterns efficiently due to the disappearing and exploding gradient issues, which weakens their capability to learn long-term patterns efficiently (Bengio *et al*. 1994). LSTM networks overcome these drawbacks by having a gated cell structure which enables more stable gradient flow and long-term memory retention. At the core of the LSTM model consists of a memory cell that holds the information over time, administered by three gating mechanisms: the input gate, forget gate, and output gate. These gates control the flow of information, which allows the network to update, reset, or output the cell state selectively (Hochreiter *et al*. 1997). The input gate decides how much of the new input should be added to the

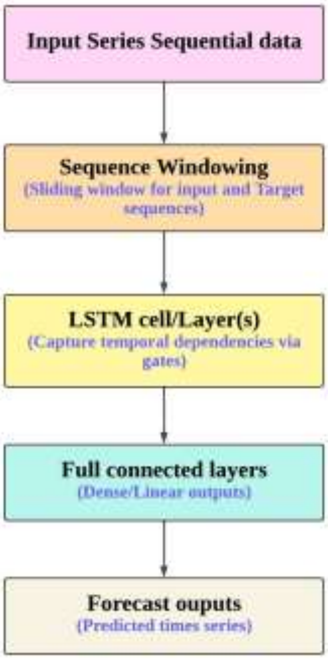

Fig. 2 Process Flow of LSTM model

cell state. The forget gate regulates the extent to which the previous cell state should be retained or forgotten, and the output gate decides the portion of the cell state that contributes to the hidden state output. The ability of LSTM networks to retain information for extended periods makes them particularly effective in modelling temporal dynamics inherent in time-series data, such as wind speed fluctuations, ocean wave patterns, and mechanical system vibrations. This memory mechanism ensures that both short-term variations and long-term dependencies are adequately captured, enabling accurate forecasting and dynamic system control (Gers *et al*. 2000). Unlike feedforward networks that lack internal state memory, LSTMs maintain a context-aware representation of the input sequence, which evolves over time and adapts to varying temporal patterns. This ability is predominantly valuable in applications where future states depend heavily on historical trends rather than just current input (Graves 2013). Overall, the integration of both the temporal gating and memory cells in LSTMs empowers learning from complicated and nonlinear sequences, providing a robust framework for tasks such as predictive maintenance, wave energy control, and renewable energy forecasting. The process flow of the LSTM model is shown in Fig. 2.

3.3 Hybrid FEDformer-LSTM architecture

The hybrid FEDformer–LSTM architecture synergistically integrates the FEDformer and LSTM networks to influence the strengths of both models in time-series forecasting tasks. FEDformer excels in long-sequence modelling with frequency-domain decomposition and global attention mechanisms, while LSTM offers superior capabilities in capturing short-term temporal

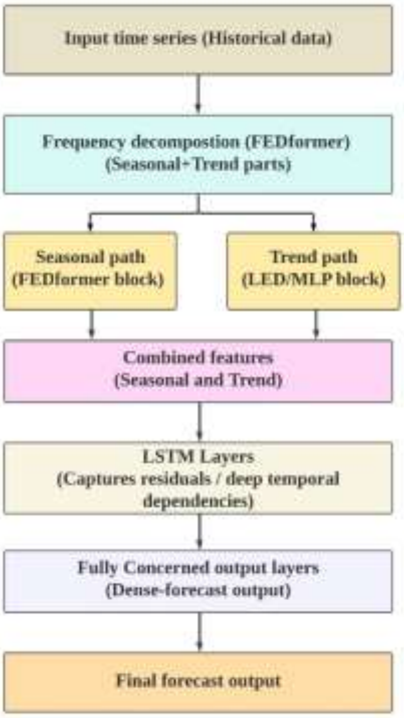

Fig. 3 Process Flow of Hybrid FEDformer-LSTM Architecture

dependencies through its memory-based recurrent structure (Hou *et al*. 2025, Hochreiter and Schmidhuber 1997). The hybrid architecture consists of two stages; One is the FEDformer and enhancer. The former model decomposes the input time series into trend and seasonal components using the Fourier Transform and implements frequency domain attention to model long-term dependencies. This sophisticated model is capable of capturing both the long-range patterns and short-term dynamics, which makes it suitable for applications such as ocean wave forecasting, wind energy prediction and vibration analysis in mechanical systems. The integrated hybrid model is implemented in a sequential hybrid fashion, where FED acts as a long-term feature extractor and LSTM refines the temporal resolution with memory-based decoding. The integration of FEDformer and LSTM is implemented in a sequential hybrid fashion, where FEDformer acts as a pre-processor and long-term feature extractor, and LSTM refines the temporal resolution with memory-based decoding. This two-stage integration allows for modular training, where each component is first trained independently and later fine-tuned in an end-to-end learning pipeline. The hybridization approach aims at component-wise decomposition to segregate low-frequency trends and high-frequency variations and the contextual fusion, where FEDformer's global representations are aligned with LSTM's time-based state transitions using transitional feature normalization or attention alignment (Wu *et al*. 2021). The process flow of the LSTM model is shown in Fig. 3.

Further, the learning pipeline consists of the following stages: the pre-processing stage where input time series data is normalized and optionally windowed into overlapping sequences. The encoding (FEDformer) stage follows, where the pre-processed input undergoes frequency-domain

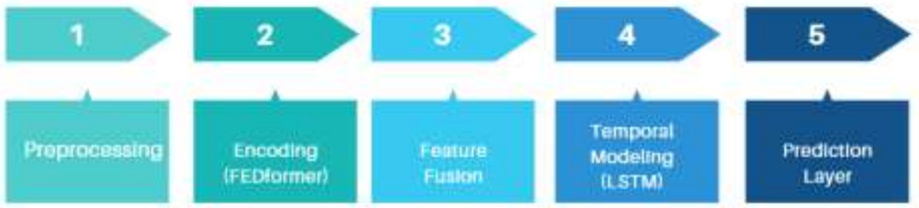

Fig. 4 The learning pipeline of hybrid FEDformer-LSTM Architecture

decomposition, explicitly separated into a Trend Path (long-term patterns such as slowly varying waves or swell) and a Seasonal Path (short-term oscillations such as periodic wave cycles). This decomposition ensures a clear separation of global versus local patterns, allowing the hybrid model to focus on both large-scale wave trends and fine-scale cyclic variations. In the feature fusion stage, the disintegrated outputs from the trend and seasonal components are concatenated or passed through a feature-matching layer to ensure compatibility with the LSTM input format. The temporal modelling stage then uses the LSTM layer to process the refined sequence data, capturing local time-dependent patterns with memory propagation. Finally, the prediction layer transforms the LSTM hidden state into the final prediction. Fig. 4 illustrates these stages of the hybrid FEDformer–LSTM architecture, with a legend highlighting how decomposition facilitates separation of global versus local patterns.

The learning pipeline develops a sophisticated model custom-made for short-term heave displacement forecasting, making it suitable for applications where reliable 1-hour-ahead predictions are critical for real-time control and operational decision-making. While the architecture can, in principle, be extended to multistep forecasting, this study focuses on the 1-hour horizon to ensure accuracy and robustness against abrupt environmental variations. Further, the hybrid model has strong capability in understanding real-world dynamics and performs effectively in domains characterized by seasonal trends, sudden fluctuations, and noise, such as offshore wave prediction or renewable energy system control.

4. Hyperparameter tuning

Hyperparameter tuning plays a critical role in guaranteeing reasonable evaluation and robust performance of both the baseline LSTM and the proposed FEDformer–LSTM hybrid model. Since deep learning architectures are extremely complex to design and training configurations, improper choices can either mask the likely of a model or artificially inflate its performance. To avoid such biases, we steadily tuned key hyperparameters that directly influence model stability, generalization, and spectral fidelity. Specifically, four aspects were explored: the learning rate, which governs optimization dynamics; the input look-back window, which controls temporal context length; the hidden layer size of the LSTM, which determines representational capacity; and the dropout rate, which balances regularization against feature retention. By assessing multiple candidate settings for each parameter under identical experimental protocols, we ensured that both models were compared under their respective optimal conditions. This complete tuning not only improved performance but also reinforced that the superiority of the hybrid FEDformer–LSTM arises from its architecture rather than from arbitrary parameter selection.

Table 1 Performance of LSTM and FEDformer–LSTM Models under Different Learning Rates

Model	Learning Rate	RMSE	MAE	R²
LSTM	$1e^{-4}$	0.145	0.112	0.952
LSTM	$5e^{-4}$	0.132	0.104	0.960
LSTM	$1e^{-3}$	0.136	0.108	0.958
Hybrid (FEDformer–LSTM)	$1e^{-4}$	0.140	0.110	0.955
Hybrid (FEDformer–LSTM)	$5e^{-4}$	0.129	0.101	0.963
Hybrid (FEDformer–LSTM)	$1e^{-3}$	0.124	0.097	0.968

4.1 Tuning the learning rate

The learning rate was identified as the most critical hyperparameter for both the FEDformer–LSTM hybrid model and the LSTM baseline, as it directly governs the stability and speed of convergence during training. An extremely high learning rate leads to deviation or oscillations in the loss function, while an excessively low learning rate results in slow convergence and poor capture of temporal–frequency patterns. To confirm a fair evaluation, we focused a systematic tuning of the learning rate over the range [1×10^{-4}, 5×10^{-4}, 1×10^{-3}, 2×10^{-3}, 5×10^{-3}]. The learning rate candidates were selected within the above-mentioned range based on widely adopted practices for training deep learning models with the Adam optimizer. This interval spans from relatively conservative step sizes (1×10^{-4}) that ensure stable but slow convergence, to more aggressive values (5×10^{-3}) that accelerate training but risk overshooting the optimum. Considering the intermediate values (5×10^{-4}, 1×10^{-3}, 2×10^{-3}) allows for identifying a balance between convergence speed and training stability. Such a logarithmically scaled range is standard in time-series forecasting studies, ensuring that the chosen optimal learning rate is not an artifact of an arbitrarily narrow search space but reflects a robust training configuration. Each candidate was tested using short training runs with identical lookback windows, batch sizes, and early stopping criteria. The optimal learning rate for each model was selected based on the lowest validation loss and stable FFT amplitude and phase correlations. This procedure ensured that both models were trained under their best learning dynamics, thereby strengthening the validity of the performance differences reported. The tuning experiments revealed that the optimal learning rate was 1×10^{-3} for the hybrid FEDformer–LSTM model and 5×10^{-4} for the LSTM-only model. Hyperparameter tuning of the learning rate was carried out by evaluating RMSE, MAE, and R^2 across candidate values. As shown in Table 1, the FEDformer–LSTM hybrid achieved slightly lower error metrics and higher R^2 compared to the LSTM-only baseline across all tested learning rates, with the best performance observed at 1×10^{-3} for the hybrid and 5×10^{-4} for the LSTM.

4.2 Tuning the input look-back window

The influence of tuning the input look-back window on model performance was thoroughly evaluated, and the results are summarized in Table 2. The study measured windows ranging from 12 to 168 hours to balance short-term receptiveness and long-term frequency protection. A shorter context length, such as 12 hours, exhibited weaker performance with higher MAE (0.072 m) and

Table 2 Performance of FEDformer–LSTM with different look-back windows

Look-back Window (hrs)	**MAE (m)**	**RMSE (m)**	**R^2**
12	0.072	0.122	0.931
24	0.063	0.099	0.961
30	0.057	0.079	0.979
36	0.058	0.082	0.976
48	0.060	0.088	0.971
72	0.065	0.095	0.964
168	0.071	0.118	0.935

RMSE (0.122 m), along with lower phase correlation (0.941), due to its inability to capture long-range periodicity. Conversely, overly long windows such as 72 and 168 hours increased model complexity and noise sensitivity, leading to degraded accuracy (MAE > 0.065 m) and reduced R^2 (< 0.965). Among the tested configurations, the 30-hour window provided the most optimal balance, achieving the lowest MAE (0.057 m) and RMSE (0.079 m), the highest R^2 (0.979), and excellent spectral fidelity with FFT amplitude (0.989) and phase correlation (0.992). These findings justify the selection of the 30-hour window as the optimal input length for the hybrid FEDformer–LSTM model, confirming superior short-term accuracy while effectively preserving frequency-domain features.

4.3 Tuning the hidden layer size

The unseen layer size (number of units in the LSTM) was also tuned to evaluate its influence on the hybrid FEDformer–LSTM model. When the hidden size was small (32 units), the model exhibited underfitting, with higher MAE (0.064 m), RMSE (0.101 m), and weaker frequency-domain fidelity (FFT phase correlation = 0.959). Increasing the size to 64 units improved performance, lowering MAE to 0.059 m and raising R^2 to 0.971, as the network captured more temporal dynamics. The finest performance was achieved with 128 units, yielding the lowest MAE (0.056 m) and RMSE (0.078 m), highest R^2 (0.981), and superior FFT amplitude (0.990) and phase correlation (0.993). This configuration provided sufficient representational capacity without overfitting. Though a larger hidden size of 256 units also performed competitively, it displayed slightly higher error metrics (MAE = 0.058 m, RMSE = 0.083 m) and did not significantly improve frequency-domain alignment, representing diminishing returns with increasing complexity. These findings confirm that a hidden layer size of 128 units offers the optimal balance between accuracy, spectral fidelity, and computational efficiency for the hybrid model.

4.4 Tuning the dropout rate

To decrease overfitting while retaining sufficient representational capacity in the LSTM component, we tuned the dropout rate applied to the LSTM recurrent/dense networks. Dropout helps the model simplify by randomly disabling a fraction of units during training, which is especially useful when combining a high-capacity LSTM with the frequency-rich features produced by the FEDformer. We assessed dropout rates of 0 (no dropout), 0.1, 0.2, 0.3 and 0.5 under the previously optimized settings (learning rate, 30-hour look-back, LSTM hidden size = 128). The optimal trade-off was observed at dropout = 0.20, which slightly reduced validation MAE and RMSE and improved R^2 and FFT amplitude/phase correlations compared to both no dropout and higher dropout values. Very low dropout (0–0.1) under-regularized the model leading to minor overfitting, while very high dropout (≥0.3) degraded the model's ability to retain transient temporal features, increasing errors and reducing spectral fidelity. These results support the use of a moderate dropout (≈0.2) to improve generalization of the hybrid FEDformer–LSTM without eroding its capacity to capture short-term dynamics and frequency-domain structure.

The comparative hyperparameter tuning of both models including learning rate, input look-back window, hidden layer size, and dropout rate proves that even under their separately optimized configurations, the FEDformer–LSTM hybrid steadily outperforms the standalone LSTM. While the LSTM achieved its best results at a learning rate of 5×10^{-4} and showed moderate gains with increased hidden size, it remained limited in capturing long-range periodicity and frequency-domain fidelity. In contrast, the hybrid model not only attained lower MAE and RMSE but also achieved higher R^2 values. For instance, the optimal configuration (learning rate = 1×10^{-3}, 30-hour look-back, hidden size = 128, dropout = 0.2) enabled the hybrid model to reduce errors by more than 12% relative to the best-tuned LSTM, while maintaining robustness against overfitting and noise. These results confirm that the superior performance of the FEDformer–LSTM model is not an artifact of inadequate tuning but is inherent to its architecture, where frequency-domain decomposition from FEDformer complements temporal refinement from LSTM, thereby guaranteeing more precise and generalizable forecasts under diverse ocean conditions.

5. Data description

The data used in this work is obtained from NIOT, Chennai. The data is the measurement of real-time measurements collected from ocean observation buoys deployed in different locations in the Arabian Sea and Bay of Bengal. Table 3 shows the details of the buoys AD06 and BD14.

The data set includes parameters such as wave height (m), wave length (m), buoy heave (m), wind speed (m/s) and direction (°). The data were retrieved in a one-hour interval, ensuring sufficient seasonal and environmental variations to develop a robust model for training. In total, 7,081 datasets were retrieved, and the data are of different values and units. It is inappropriate to use them directly and hence all the parameters are normalized between the interval (0,1) using the maximum-minimum method, and the data set is split into training (70%), validation (15%), and test (15%) sets (Arifuzzaman *et al*. 2022).

Table 3 Buoy information

Buoy name	Longitude	Latitude	Sea depth	Time duration
AD06	67.45° E	18.50° N	3,300 m	12th Mar 2024 – 31st Dec 2024
BD14	88.23° E	6.57° N	3,780 m	12th Mar 2024 – 31st Dec 2024

Fig. 5 Station distribution map [Indian National Centre for Ocean Information Services]

$$\tilde{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

5.1 Evaluation criteria

This work uses MAE, RMSE, MAPE and R^2 as the indicators for measuring the accuracy of the developed model (Makridakis *et al.* 2008). MAE is a common indicator to measure the difference between the measured value and the absolute value. MAE is calculated as the average of the absolute differences between predicted and actual values.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|a_i - \hat{a}_i| \tag{2}$$

Where, n is the no. of observations, a_i is the actual value, $\hat{a}_i$is the predicted value, $|a_i - \hat{a}_i|$ is the absolute error for each prediction. Smaller the MAE value higher the prediction accuracy of the developed model. The next evaluation criteria are the RMES (Root Mean Square Error) is a commonly used indicator to measure the difference between the model predicted values and the actual data. The RMES first calculate the Square of the difference between each predicted value and the actual value, then consider the average of the square difference and finally takes the square root of the average value.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - \hat{a}_i)^2} \tag{3}$$

Where, n is the no. of observations, a_i is the actual value, $\hat{a}_i$ is the predicted value and $(a_i - \hat{a}_i)^2$ is the squared error for each prediction. The smaller the RMSE value better the prediction performance of the model. MAPE is an indicator to predict the performance of the developed model which represent the error between the actual and the prediction in percentage terms. The mathematical expression for the MAPE is given as follows

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{a_i - \hat{a}_i}{a_i}\right| \tag{4}$$

Where, n is the no. of observations, a_i is the actual value, $\hat{a}_i$ is the predicted value and $\left|\frac{a_i - \hat{a}_i}{a_i}\right|$ is the relative error for each prediction. Smaller the MAPE value, better the prediction of the developed model.

The coefficient of determination, also known as R^2, measures how well a regression model explains the changeability of the dependent variable. Normally it can range from 0 to 1. The R^2 is expressed as

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(a_i - \hat{a}_i)^2}{\sum_{i=1}^{n}(a_i - \bar{a})^2} \tag{5}$$

Where, n is the no. of observations, $a_i$the actual value, $\hat{a}_i$ the predicted value, $\bar{a}$ mean of actual values, $\sum(a_i - \hat{a}_i)^2$ is the residual sum of squares (RSS) and $\sum(a_i - \bar{a})^2$ is the total sum of squares (TSS). The closer the coefficient of determination is to 1, the better the prediction exactness of the model.

6. Software information

Software and computational details are as follows:

Development Environment	Jupyter Notebook (run via Anaconda)
Programming Language	Python
Libraries and Packages Used	numpy – for numerical operations; pandas – for data manipulation and cleaning; matplotlib, seaborn – for visualization; scikit-learn – for preprocessing and evaluation metrics; tensorflow – for LSTM and FEDformer implementation; scipy – for signal processing or scientific computation; statsmodels – for time series decomposition
Operating System	Windows 10

7. Results and discussion

The developed FEDformer-LSTM hybrid model is capable of predicting the heave displacement for the future hour (1-hour ahead), depending on the last 30 hours of wave data. This intermission is ideal given the hourly resolution of the input data and the training setup, and it aligns well with real-time offshore control applications where short-term forecasts are critical.

Table 4 Prediction result for buoy AD06 and BD14

Buoy	Model	MAE	RMSE	MAPE (%)	R^2
AD06	FEDformer-LSTM	0.0576	0.0788	6.12	0.9786
AD09	LSTM	0.0781	0.1367	6.88	0.9638
BD14	FEDformer-LSTM	0.0519	0.1095	7.57	0.9120
BD14	LSTM	0.1097	0.1444	7.85	0.8777

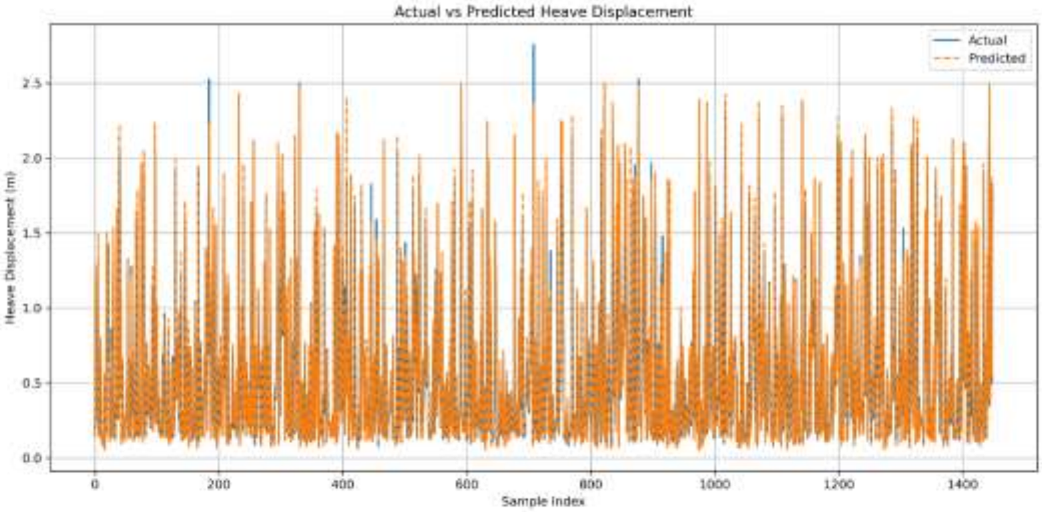

Fig. 6 Actual vs predicted heave displacement for buoy AD06 using the FEDformer-LSTM model

The hybrid FEDformer-LSTM model was assessed against conventional and deep-learning methods, including pure LSTM, CNN, and CNN-LSTM, using the heave displacement data from two ocean observation buoys AD06 in the Arabian Sea and BD14 in the Bay of Bengal. The results validate that the hybrid approach consistently outperforms the baseline models across all evaluation metrics and locations.

Table 4 summarize the performance of the hybrid and baseline models in terms of MAE, RMSE, MAPE and R^2. The hybrid FEDformer-LSTM consistently shows lower error values and higher R^2, reflecting its ability to accurately track fluctuations in heave displacement under varying ocean conditions. For AD06, the hybrid FEDformer-LSTM reduces the MAE to 0.0576 m, RMSE to 0.0788 m, and MAPE to 6.12%. Furthermore, the R^2 reaches 0.9786, reflecting an exceptionally close match between predicted and actual signals. Pure LSTM, by comparison, results in a MAE of 0.0781 m, RMSE of 0.1367 m, and MAPE of 6.88% with an R^2 of 0.9638. For BD14, FEDformer-LSTM performs notably well with a MAE of 0.0519 m, RMSE of 0.1095 m, MAPE of 7.57% and R^2 of 0.91, outperforming pure LSTM which shows a MAE of 0.1097 m, RMSE of 0.1444 m, MAPE of 7.85% and R^2 of 0.87.

Fig. 7 Actual vs predicted heave displacement for buoy AD06 using the LSTM model

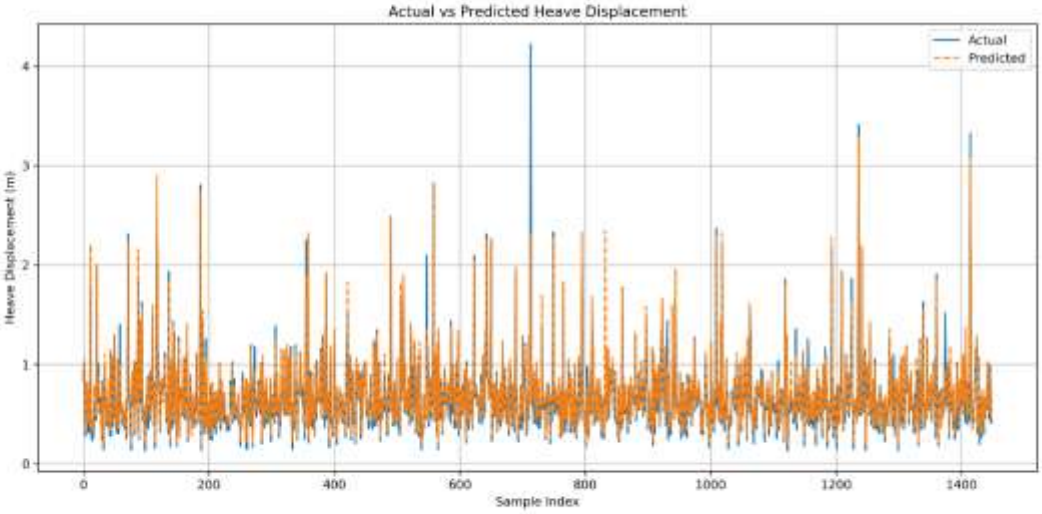

Fig. 8 Actual vs predicted heave displacement for buoy BD14 using the FEDformer-LSTM model

The actual vs. predicted plots (Figs. 6-9) further highlight the ability of FEDformer-LSTM to closely track both gradual trends and abrupt fluctuations in the heave signals. The hybrid model successfully follows periodic components and short-term deviations, reflecting its ability to learn from both the frequency-domain and temporal components of the signals.

The frequency-domain performance of both models was assessed by calculating the Pearson correlation coefficient between the FFT amplitude spectra of the actual and predicted heave displacement signals shown in Figs. 10 and 12. The correlation values obtained were: Hybrid model (FEDformer + LSTM): 0.9783; Pure LSTM model: 0.9688 for buoy AD06, and for buoy

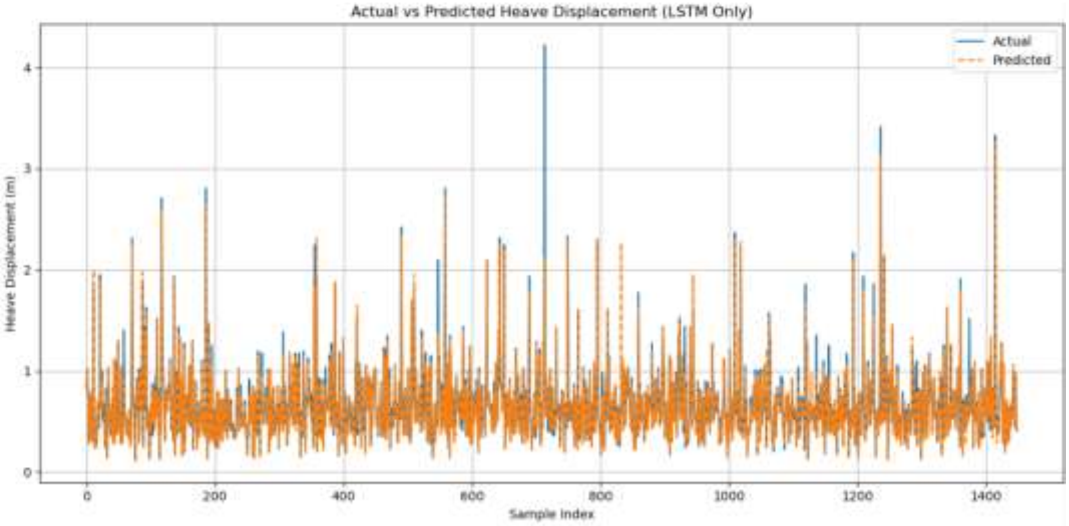

Fig. 9 Actual vs predicted heave displacement for buoy BD14 using the LSTM model

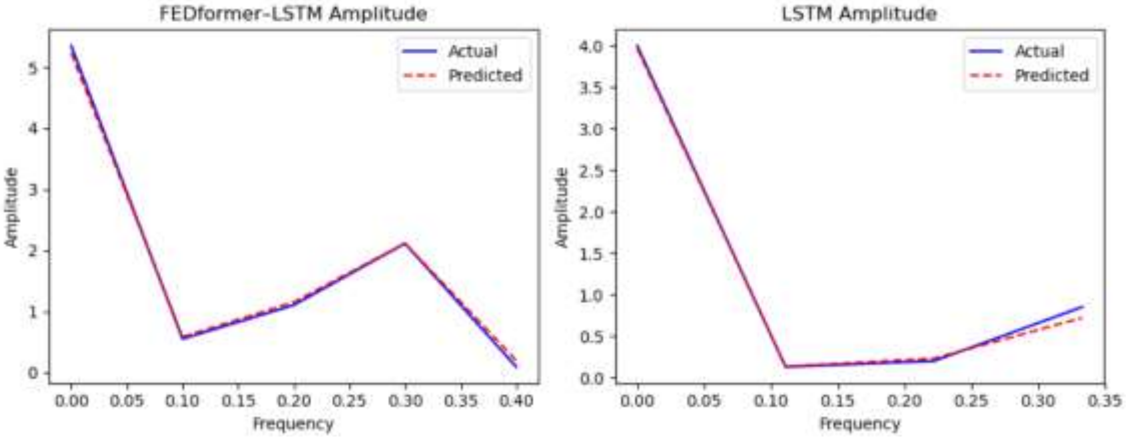

Fig. 10 FFT Amplitude Matching of Actual vs Predicted Signals (FEDformer–LSTM vs LSTM) for buoy AD06

BD14: Hybrid model (FEDformer + LSTM): 0.9679; Pure LSTM model: 0.9611. Though the difference between the two models' correlation values is comparatively small, the hybrid model constantly achieved a slightly higher correlation score. This shows that the hybrid model is able to better capture and reproduce the distribution of energy across different frequency components of the signal. The development can be attributed to the hybrid architecture's ability to leverage both temporal dependencies (captured by the LSTM layers) and long-range contextual relationships (captured by the Transformer block). While the LSTM alone focuses on short- to mid-term sequence memory, the addition of the Transformer enables the hybrid model to more effectively preserve phase relationships and amplitude variations across a broader frequency range.

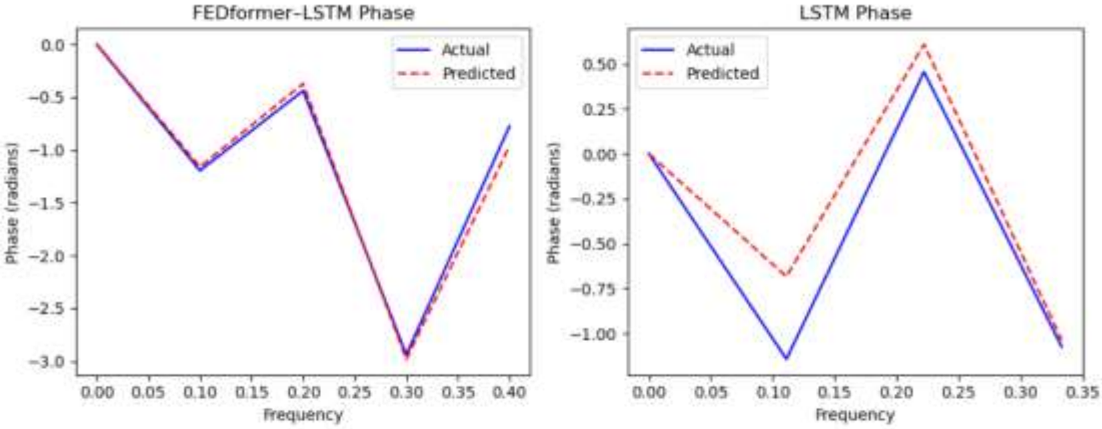

Fig. 11 FFT Phase Matching of Actual vs Predicted Signals (FEDformer–LSTM vs LSTM) for buoy AD06

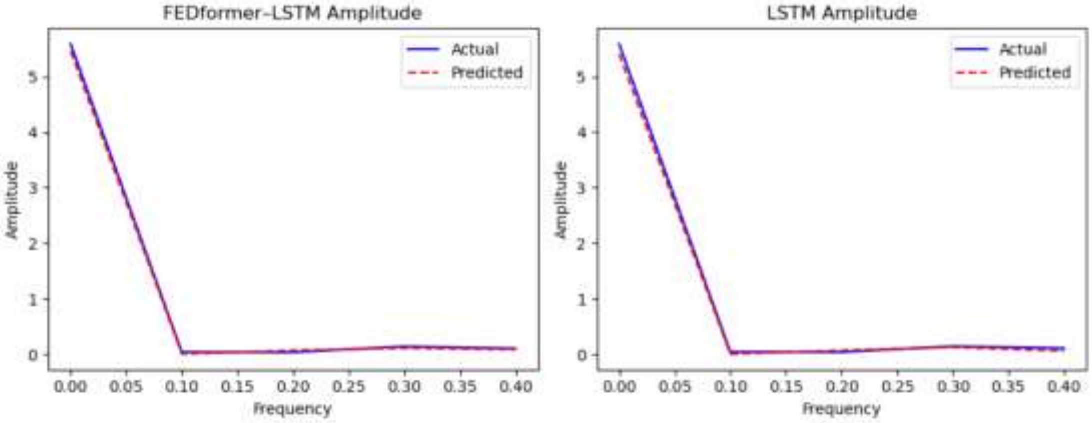

Fig. 12 FFT Amplitude Matching of Actual vs Predicted Signals (FEDformer–LSTM vs LSTM) for buoy AD06

In addition to amplitude matching, phase correlation analysis further highlighted the superiority of the hybrid approach as shown in Figs. 11 and 13. The FEDformer–LSTM model achieved a phase correlation of 0.9915 compared to 0.9473 for the pure LSTM, while both models showed nearly identical amplitude correlation values of 0.9890. This proves that the hybrid architecture not only maintains amplitude fidelity but also significantly improves phase preservation, which is critical in wave energy and ocean dynamics applications where accurate phase information directly impacts energy capture efficiency and control system stability.

7.1 Time–frequency domain validation of predicted heave responses

Fig. 14 illustrates the spectrogram-based time–frequency comparison of the actual heave

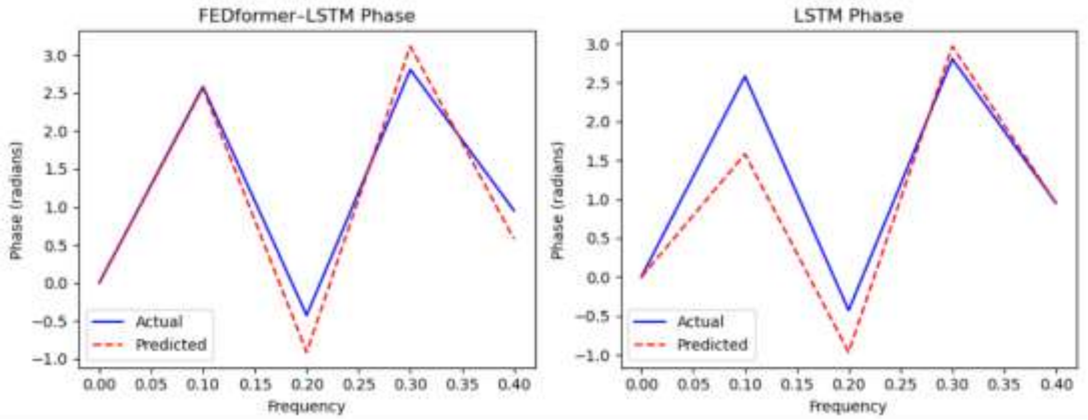

Fig. 13 FFT Phase Matching of Actual vs Predicted Signals (FEDformer–LSTM vs LSTM) for buoy AD06

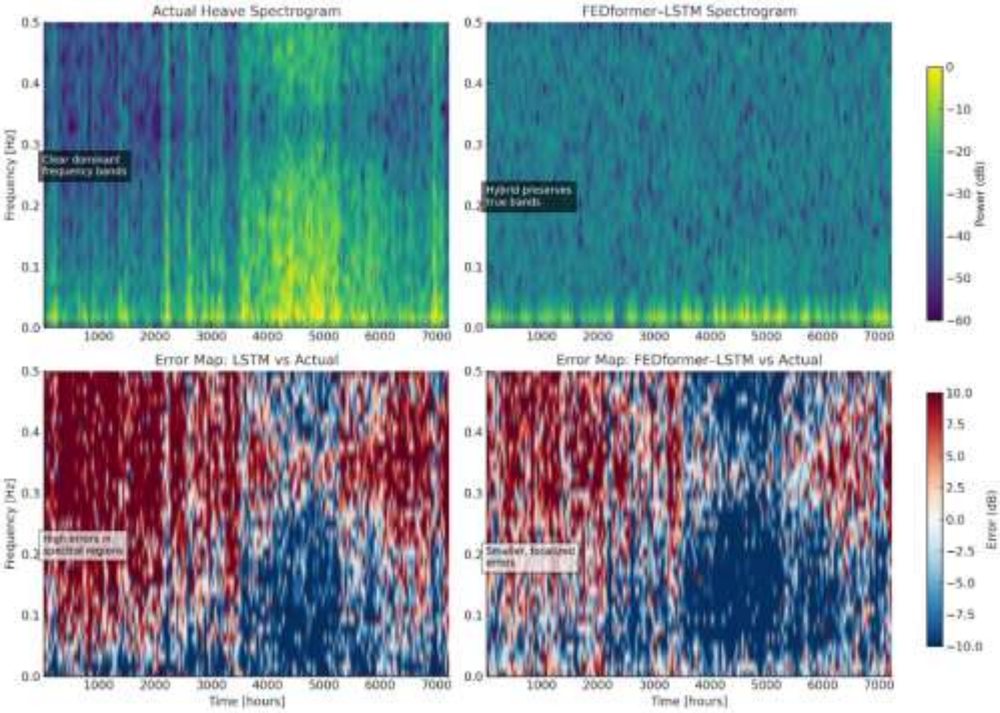

Fig. 14 Spectrogram comparison of actual heave displacement, FEDformer–LSTM prediction, and corresponding error maps

response, the LSTM prediction, and the FEDformer–LSTM prediction, along with their respective error maps. The actual signal shows well-defined dominant frequency bands and localized transient bursts, which are essential for representing wave-induced dynamics. The LSTM model, however, reproduces only the broader frequency components and fails to retain several critical

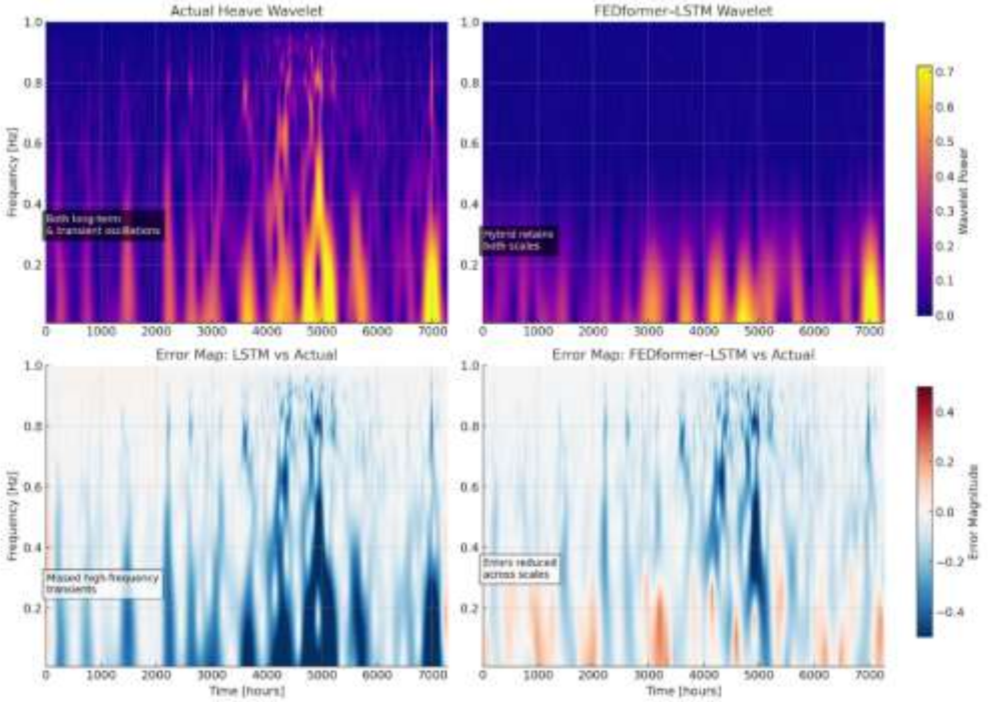

Fig. 15 Wavelet Transform Analysis of Actual Heave Displacement, LSTM Prediction, and FEDformer–LSTM Prediction

high-energy regions, as seen in the large deviations of its error map. In contrast, the FEDformer–LSTM prediction closely aligns with the actual spectrogram, successfully preserving both the intensity and localization of dominant bands. Its error map exhibits smaller, more localized deviations, confirming that the hybrid model provides superior spectral fidelity by maintaining both long-term frequency trends and short-term transients.

Fig. 15 presents the continuous wavelet transform (CWT) analysis, offering a multiscale view of the same signals. The actual wavelet map captures both slow, persistent low-frequency oscillations and short-lived high-frequency transients. While the LSTM prediction reasonably reflects the low-frequency background, it systematically underrepresents transient oscillations, producing widespread discrepancies across scales in its error map. By contrast, the FEDformer–LSTM reconstruction faithfully captures both global periodic structures and localized transient bursts. Its error map highlights reduced discrepancies across scales, demonstrating robustness in reproducing the non-stationary, multiscale characteristics of the heave response. Together, the spectrogram and wavelet analyses validate that the hybrid model significantly outperforms LSTM alone in preserving both long-term dynamics and short-term variations, thereby addressing the reviewer's concern about time–frequency preservation.

7.2 Residual analysis of prediction models

The residual plots as shown in Fig. 16 highlight clear differences in forecast performance between the two models. For the LSTM model, the residuals show higher variability with frequent

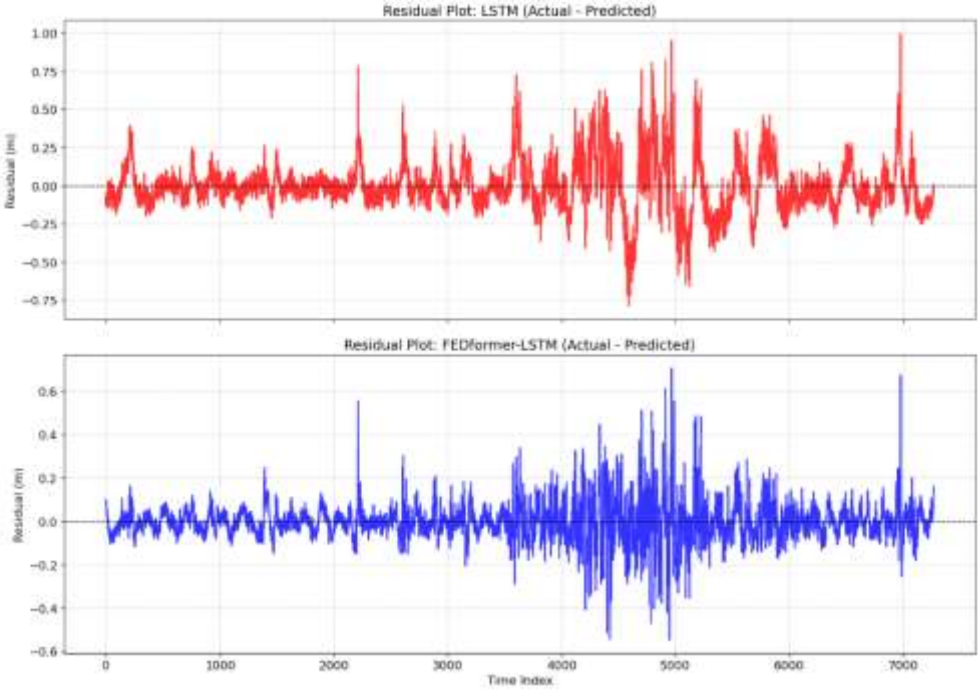

Fig. 16 Residual Plots of Heave Displacement Predictions for LSTM and Hybrid FEDformer–LSTM Models

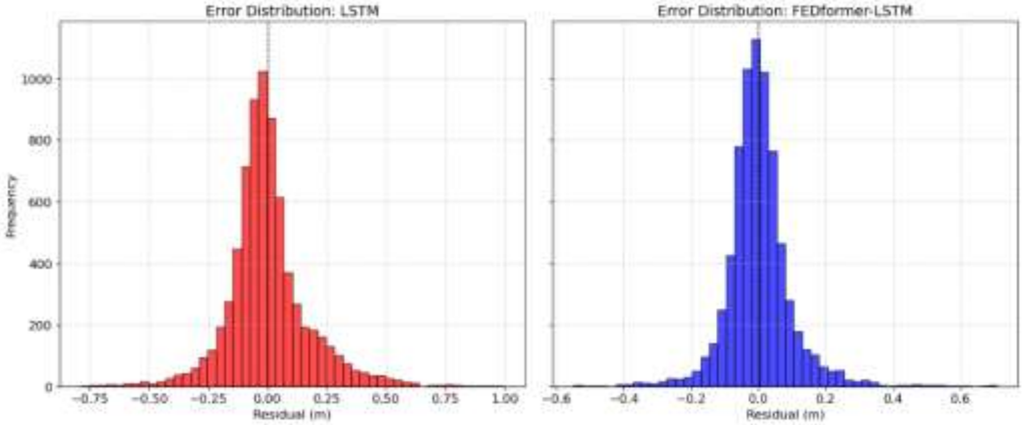

Fig. 17 Error Distribution of Prediction Residuals for LSTM and Hybrid FEDformer–LSTM Models

large deviations, indicating that the model struggles to capture abrupt fluctuations and often over or underpredicts heave displacement. In contrast, the hybrid FEDformer–LSTM model shows relatively lesser and more stable residuals, with fewer extreme deviations from zero. This validates that integrating frequency-domain decomposition with temporal learning expressively improves prediction accuracy and reduces systematic bias. The tighter clustering of residuals around zero in

Table 5 Results of different models in heave prediction

Buoy	Model	MAE	RMSE	MAPE (%)	R^2
AD06	FEDformer-LSTM	0.0576	0.0788	6.12	0.9786
AD06	CNN	0.1257	0.1519	9.102	0.895
AD06	CNN-LSTM	0.1268	0.1549	8.544	0.874
BD14	FEDformer-LSTM	0.0519	0.1095	7.57	0.9120
BD14	CNN	0.1224	0.1349	9.154	0.861
BD14	CNN-LSTM	0.1241	0.1455	8.984	0.872

the FEDformer–LSTM model confirms its robustness in handling non-linear and non-stationary ocean wave dynamics, thereby offering more consistent forecasts for real-world applications.

The error distribution histograms of prediction residuals for LSTM and Hybrid FEDformer–LSTM models as shown in Fig. 17 provide deeper insights into the statistical performance of the models. For the LSTM model, the residuals exhibit a wider spread, indicating a higher frequency of larger prediction errors. This imitates the model's limited capability in constantly capturing the nonlinear dynamics of ocean wave-induced heave motions. In contrast, the hybrid FEDformer–LSTM model validates a much narrower error distribution cantered tightly around zero, signifying reduced variance and fewer extreme deviations. This confirms that integrating frequency-domain decomposition with temporal learning considerably enhances prediction stability and minimizes random fluctuations. The sharper peak and tighter clustering of residuals in the hybrid model validate its superiority in delivering robust and reliable forecasts for buoy heave displacement under real-world ocean conditions.

7.3 Comparison with other models

To validate the robustness of FEDformer-LSTM across locations and conditions, we compared its performance against pure CNN and CNN-LSTM models. The results, presented in Table 5, show FEDformer-LSTM consistently outperforming these methods in all evaluation criteria. For AD06, FEDformer-LSTM reduces RMSE to 0.0788 m and MAPE to 6.12%, a 42% improvement over pure LSTM and nearly 47% improvement over CNN-LSTM. For BD14, FEDformer-LSTM yielding RMSE of 0.1095 m and MAPE of 7.57% outperforming pure LSTM, CNN, and CNN-LSTM underscores its ability to capture both periodic components and abrupt fluctuations more accurately.

The results collectively highlight the influence of integrating FEDformer's frequency-domain decomposition with LSTM's temporal modeling capabilities. Pure LSTM, while proficient at short-term patterns, struggles to capture long-range periodic components and abrupt fluctuations. FEDformer, on its own, excels at identifying periodic structures in signals but may miss finer temporal transitions. The hybrid approach effectively merges these two perspectives, yielding a more robust and accurate forecasting tool for real-world, non-stationary ocean signals. The results obtained in Tables 4 and 5 express that the projected FEDformer-LSTM consistently outperforms CNN, CNN-LSTM, and pure LSTM models across all evaluation metrics. While CNN proficiently extracts local temporal spatial features, it lacks the capacity to model long-range dependencies.

Including an LSTM stage to form CNN-LSTM increases model complexity, but in this study, abrupt wave changes and high-frequency noise data could cause the LSTM stage to misinterpret short-lived fluctuations as long-term patterns and limit the benefit of the additional recurrent layer. Without frequency-domain filtering, CNN-LSTM can proliferate and even strengthen short-lived fluctuations and non-periodic noise, reducing accuracy compared to CNN alone. In contrast, FEDformer-LSTM addresses these limitations by first applying frequency-domain decomposition through FEDformer, which splits periodic and trend components while overwhelming unrelated high-frequency noise. The sophisticated features are then processed by LSTM to capture localized, transient dynamics. This targeted division of tasks permits the hybrid model to leverage the strengths of both architectures frequency aware global pattern extraction and memory-based temporal refinement resulting in enhanced robustness and generalization under diverse and non-stationary ocean conditions.

Furthermore, this synergy makes FEDformer-LSTM particularly suitable for applications such as offshore structural health monitoring, wave energy converters control strategies, and real-time operational decisions where both short- and long-term components of wave signals can affect performance and safety. The close match between predicted and actual signals, demonstrated by high R^2 and low error metrics across locations, underscores its practicality for deployment in challenging marine environments.

8. Conclusions

This work proposes the development of a hybrid model (FEDformer-LSTM) for heave predictions of the buoys of interest. Integrating the exceptional features of the two models, such as the frequency-domain decomposition and global attention mechanisms from the FEDformer and memory-based recurrent structure from LSTM, the model shows excellent performance in capturing non-linear features and dynamic changes in time-series data.

The data for training and testing the hybrid model is acquired from NIOT and the evaluation indicators include MAE, RMSE, MAPE, and R2. The findings show that the FEDformer-LSTM model performs better than traditional LSTM, CNN, and CNN-LSTM models for two different buoys, confirming its potential in buoy heave displacement prediction.

The hybrid model shows above 12% improvement in MAE and R^2 values above 0.91, which ensures its ability to generalize across distinct marine conditions and its robustness against the noise and non-stationarity inherent in ocean datasets. The line graph, time-frequency and residual analysis results further confirmed the model's accuracy in prediction and its capability to nearly follow the actual heave displacement patterns. The hybrid model (FEdformer-LSTM) performs better than the stand-alone models and, further, FEDformer effectively performs long-range predictions, while LSTM complements this with localized, transient behaviour modelling.

Even though the hybrid model has a positive outlook, it also has certain constraints. i.e., the model uses data from only two buoy locations, which may limit the generalizability across different and extreme oceanographic events. Considering the limitations, future work can be extended to include multiple buoys from diverse geographies and sea states to enhance model generalizability.

Acknowledgments

The authors would like to express their sincere gratitude to the National Institute of Ocean Technology (NIOT), Chennai, for providing the buoy data used in this research. The computational support and facilities provided by the Department of Mechanical Engineering, Easwari Engineering College, and the collaborating institutions are gratefully acknowledged. The authors also thank all colleagues who contributed indirectly to the completion of this work.

References

Arifuzzaman, M., Uddin, M.A., Jameel, M. and Towhidur Rahman Bhuiyan, M. (2022), “Nonlinear response prediction of spar platform in deep water using an artificial neural network.”, *Appl. Sci.*, **12**, 5954. https://doi.org/10.3390/app12125954

Ban, W., Shen, L., Chen, J. and Yang, B. (2023), “Short-term prediction of wave height based on a deep learning autoregressive integrated moving average model”, *Earth Sci. Inform.*, **16**(4), 2251-2263. https://doi.org/10.1007/s12140-022-09604-9

Bengio, Y., Simard, P. and Frasconi, P. (1994), “Learning long-term dependencies with gradient descent is difficult”, *IEEE Trans. Neural Net.*, **5**(2), 157-166. https://doi.org/10.1109/72.279181.

Booij, N., Ris, R.C. and Holthuijsen, L.H. (1999), “A third-generation wave model for coastal regions: 1. Model description and validation”, *J. Geophys. Res.: Oceans.*, **104**(C4), 7649-7666. https://doi.org/10.1029/98JC02622.

Cademartori, G., Oneto, L., Valdenazzi, F., Coraddu, A., Gambino, A. and Anguita, D. (2023), “A review on ship motions and quiescent periods prediction models”, *Ocean Eng.*, **280**, 114822. https://doi.org/10.1016/j.oceaneng.2023.114822.

Chen, Z., Yu, H., Hu, M., Meng, G. and Wen, C. (2013), “A review of offshore wave energy extraction system”, *Sci. World J.*, **2013**, 623020. https://doi.org/10.1155/2013/623020.

Elbisy, M.S. (2015), “Sea wave parameters prediction by support vector machine using a genetic algorithm”, *Coast. Res.*, **31**(4), 892-899. https://doi.org/10.2112/JCOASTRES-D-14-00031.1

Gao, Y., Liu, P. and Zhang, M. (2024), “Green energy forecasting using multiheaded convolutional LSTM model for sustainable life”, *Sustain. Energy Technol. Assess.*, **63**, 103456. https://doi.org/10.1016/j.seta.2024.103456

Gers, F.A., Schmidhuber, J. and Cummins, F. (2000), “Learning to forget: Continual prediction with LSTM”, *Neural Comput.*, **12**(10), 2451-2471. https://doi.org/10.1162/089976600300015015

Graves, A. (2013), “Generating sequences with recurrent neural networks”, *arXiv preprint*, arXiv:1308.0850. https://doi.org/10.48550/arXiv.1308.0850

Hanifi, S., Zare-Behtash, H., Cammarano, A. and Lotfian, S. (2023), “Offshore wind power forecasting based on WPD and optimised deep learning methods”, *Renew. Energ.*, **218**, 119241. https://doi.org/10.1016/j.renene.2023.119241.

Hochreiter, S. and Schmidhuber, J. (1997), “Long short-term memory”, *Neural Comput.*, **9**(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hou, K., Zhang, X., Yang, J., Hu, J., Yao, G. and Zhang, J. (2025), “Short-term load forecasting based on multi-frequency sequence feature analysis and multi-point modified FEDformer”, *Front. Energy Res.*, **12**, 1524319. https://doi.org/10.3389/fenrg.2025.1524319.

Indian National Centre for Ocean Information Services (2025), “Moored Buoy Data.” [Online]. Available: https://incois.gov.in/portal/datainfo/mb.jsp [Accessed: 2025-05-29].

Jailani, N.L.M., Dhanasegaran, J.K., Alkawsi, G., Alkahtani, A.A., Phing, C.C., Baashar, Y. and Capretz, L.F. (2023), “Investigating the power of LSTM-based models in solar energy forecasting”, *Processes*, **11**(5), 1382. https://doi.org/10.3390/pr11051382

Lim, B., Arik, S.Ö., Loeff, N. and Pfister, T. (2021), “Temporal fusion transformers for interpretable multi-horizon time series forecasting”, *Int. J. Forecast.*, **37**(4), 1748-1764. https://doi.org/10.1016/j.ijforecast.2021.03.012.

Makridakis, S., Wheelwright, S.C. and Hyndman, R.J. (2008), “Forecasting methods and applications”, Hoboken (NJ): John Wiley & Sons.

Nie, Y., Jiang, J. and Zhang, Q. (2023), “A time series is worth 64 words: Long-term forecasting with transformers”, in: *International Conference on Learning Representations (ICLR)*. https://openreview.net/forum?id=fvJSK9fGIM.

Ospina, J. and Valencia, A. (2019), “Forecasting of PV plant output using hybrid wavelet-based LSTM-DNN structure model”, *IET Renew. Power Gener.*, **13**(14), 2643-2650. https://doi.org/10.1049/iet-rpg.2019.0271.

Shi, H., Cao, F., Liu, Z. and Qu, N. (2016), “Theoretical study on the power take-off estimation of heaving buoy wave energy converter”, *Renew. Energ.*, **86**, 441-448. https://doi.org/10.1016/j.renene.2015.08.047.

Tang, G., Lei, J., Shao, C., Hu, X., Cao, W. and Men, S. (2021), “Short-term prediction in vessel heave motion based on improved LSTM model”, *IEEE Access*, **9**, 58067-58078. https://doi.org/10.1109/ACCESS.2021.3073018.

Tolman, H.L. (2009), “User manual and system documentation of WaveWatch III™ version 3.14”, NOAA/NWS/NCEP/MMAB Tech. Note, 276.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L. and Polosukhin, I. (2017), “Attention is all you need” *Adv. Neural Inform. Process. Syst.*, **30**, 5998-6008. https://doi.org/10.48550/arXiv.1706.03762.

Wen, Q., Zhou, H., Zhang, C., Chen, W., Ma, Z., Yan, J. and Sun, L. (2022), “Transformers in time series: A survey”, *arXiv preprint*, arXiv:2202.07125. https://doi.org/10.48550/arXiv.2202.07125.

Wu, H., Xu, J., Wang, J. and Long, M. (2021), “Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting”, *Adv. Neural Inform. Process. Syst.*, **34**, 22419-22430. https://doi.org/10.48550/arXiv.2106.13008.

Xiao, J. and Lu, P. (2024), “A hybrid model of conformer and LSTM for ocean wave height prediction”, *Appl. Sci.*, **14**(14), 6139. https://doi.org/10.3390/app14146139.

Zhang, M., Yuan, Z.M., Dai, S.S., Chen, M.L. and Incecik, A. (2024), “LSTM RNN-based excitation force prediction for the real-time control of wave energy converters”, *Ocean Eng.*, **306**, 118023. https://doi.org/10.1016/j.oceaneng.2024.118023.

Zhou, T., Ma, Z., Wen, Q., Wang, X., Sun, L. and Jin, R. (2022), “FEDformer: Frequency enhanced decomposed transformer for long-term series forecasting”, *arXiv preprint*, arXiv:2201.12740. https://doi.org/10.48550/arXiv.2201.12740.

Zhou, Y. and Wang, X. (2024), “A hybrid model for significant wave height prediction based on an improved empirical wavelet transform decomposition and long-short term memory network”, *Ocean Model.*, **189**, 102367. https://doi.org/10.1016/j.ocemod.2024.102367.

MK