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SHORT-TERM WAVE FORECASTING USING AI MODELS FOR THE OPERATION OF NAVIGATION CHANNELS AND SEAPORTS IN VIETNAM

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Abstract

The paper presents an overview of artificial intelligence (AI) models, also known as artificial neural networks (ANNs), applied in short-term wave forecasting and ship motion prediction models under the influence of waves, serving the operation of navigation channels and seaports in Vietnam. The process is divided into two steps: first, AI models are used to forecast short-term waves. In this part, different AI-based wave forecasting models are analyzed and compared, and the most suitable model is selected for wave prediction. Then, the predicted waves are input into the ship motion prediction model as a basis for evaluating scenarios of ship entry and exit in the channel. The forecasting models developed in this study are based on datasets collected over many years in the Quảng Ninh coastal area and can be applied to the operation of Cái Lân, Vạn Ninh, and Cẩm Phả seaports. The computational results and analysis show that the application of AI models for short-term wave forecasting achieves very high accuracy. Among them, the Long Short-Term Memory (LSTM) model provides the most accurate results within the shortest computation time.

Keywords: *Wave forecasting, AI model, ANNs, LSTM, Seaports, Navigation channels.*

1. Overview

1.1. The Need for short-term wave forecasting in maritime and port operations

Forecasting waves a few hours before a ship enters ports is essential to ensure safety during tugboat operations, while also enhancing the ship's cargo capacity. This issue has received considerable attention from experts, maritime businesses, and government authorities in Vietnam. Several short-term wave forecasting methods [1][2] currently used worldwide demand extensive measurements and surveys, incur high operational costs, and involve technologies that are not yet fully accessible or feasible to master under current conditions.

Therefore, applying AI models for short-term wave forecasting to support port planning and operations is one of the most effective and suitable approaches for Vietnam's conditions. Along with "Big Data", artificial intelligence (AI), artificial neural networks (ANNs), and deep neural learning networks (DNNL) are increasingly applied in various aspects of life, especially in forecasting. Wave forecasting using AI/ANNs, or hybrid approaches, has been widely studied and applied around the world for wave computation and prediction [3], [4], [5], [6], [7].

In previous years, the limited availability of wave measurement data posed challenges to applying this method. However, the current datasets of wave measurements and surveys at Vietnamese ports and maritime channels are now sufficiently large to make the method feasible.

The application of the big data and AI models is an inevitable trend across all fields of life. In port engineering, however, their application has lagged behind other sectors. Therefore, the use of DNNL models for shallow-water wave forecasting serves as an initial step for further research, including:

- Short-term wave forecasting to support maritime channel and port operations;
- Forecasting navigational risks along a route or within a study area;
- Forecasting cargo and transportation activities.

Many numerical models for wave propagation are currently in use in Vietnam, such as SWAM. The differences between the DNNL model and numerical models are presented in Table 1.

From the above comparison, it can be seen that, compared with numerical models, AI models have the following advantages:

Less costly since topographic survey data are not required;

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Table 1. Comparison between forecasting methods using ANNs and traditional mumerical models

No.	Content	AI/ANNs (DNNL)	Numerical Models
1	Input data		
1.1	Topographic survey	Not required	Required
	Water level data	Collected	Collected
1.2	Wave and wind data in deep-water areas (e.g., NOAA)	Wind data extracted from NOAA	Wave data extracted from NOAA
1.3	Local wind data (at project site)	Wind data from the nearest observation station	Wind data from the nearest observation station
2	Measured wave data for validation	Required	Required
3	Forecasting results	AI network outputs	Wave propagation models
4	Reliability	High	Dependent on model expert
5	Computation time	Very fast	Longer
6	Implementation cost	Lower	Higher

Higher reliability as they do not depend on the modeler's expertise;

Faster computation time;

Easier operation, without the need for specialized modeling experts;

Lower implementation cost;

Greater accuracy in complex problems, such as those involving complicated topography and geomorphology affecting navigation channels.

However, the limitation of this method is that it can only forecast waves at predefined finite points (rather than producing a full wave field), and it requires measured data for model validation.

1.2. Procedure for developing a forecasting model for maritime and port operations

The process of constructing a short-term wave forecasting model and its application in maritime channel and port operations is illustrated in Figure 1.

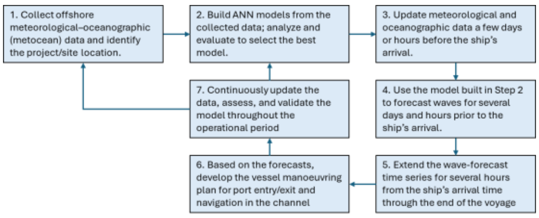

Figure 1. Flowchart of Model Development Steps and Forecasting Procedure

2. Overview of AI/ANN (Artificial Neural Network) models for short-term wave Forecasting

Artificial neural networks (ANNs) are used in modeling complex relationships between inputs and outputs or in detecting patterns within data. Essentially, they are designed to simulate the functioning of the human brain. In general, ANNs are divided into three parts or layers, defined by a set of three parameters, as illustrated in Figure 2.

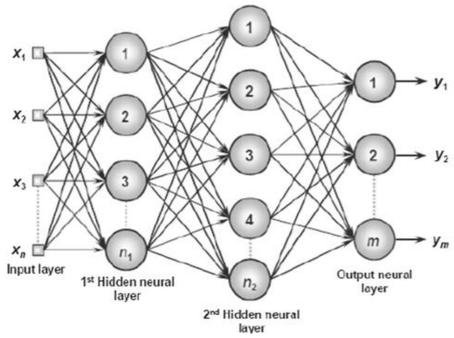

Figure 2. Structure of a Simple Neural Network in an AI Model (source: Internet)

The signals (information) $x_1, x_2..., x_n$ are received by the neural network (similar to the way human neural systems function). Based on the "experience" or "memory" stored (here represented as hidden layers), the neural network generates output signals (information), denoted as $y_1, y_2,...y_m$. Thus, given an input signal matrix $X(i,t)$ (where t is the time variable) and an output signal matrix $Y(i,t)$, the parameters of the neural network can be determined through trial-and-error or iterative learning, commonly referred to as machine learning.

A limitation of traditional neural networks is that the number of hidden layers is restricted to about 2-3 layers, which reduces the model's accuracy when applied to complex problems (e.g., object recognition). Therefore, deep neural networks (DNNs), with up to hundreds of hidden layers, have been developed to improve both processing speed and model accuracy.

Table 2. Scope of Application of ANN Models/Networks

Model Type	Scope of Application	Limitations
FNN	FNN is a simple and intuitive choice for predicting sea wave conditions, where the inputs are environmental factors (e.g., wind speed, pressure) and the outputs are predicted wave height, direction, or other state variables.	FNN does not capture temporal dependencies, which are crucial for predicting the evolution of wave states over time.
CNN	When wave data are available in spatial grid format (e.g., satellite images of ocean waves or oceanographic data), CNNs can be used to extract spatial features from these images or 2D grids to predict wave patterns.	CNNs do not capture temporal dependencies, which are crucial for predicting the evolution of wave states over time.
RNN	RNNs are designed for sequential data and are a better choice than FNNs for wave forecasting since they can retain past inputs (previous time steps) and learn from them. This is important as sea wave states are time-dependent.	Traditional RNNs may struggle to learn long-term dependencies due to the vanishing gradient problem.
LSTM	The best choice for time-series data. LSTMs are particularly effective for forecasting sea wave states because they can learn both short-term and long-term dependencies in sequential data. LSTMs can predict wave height, period, and direction by processing multiple time steps, thereby improving accuracy and robustness in dynamic environments.	Model training time is long, and implementation cost is high.
HM	Overcomes the limitations of the above models and can be tailored to specific case studies.	Dependent on the specific problem.

To date, the application of AI for ocean wave forecasting has been widely studied. The differences in research approaches mainly lie in the type of AI model applied, the measurement and data sources used for AI training, and the extent to which wave forecasting results can be integrated into port operations. Specifically, these studies can be classified into the following groups:

2.1. Feedforward Neural Network (FNN)

FNN is one of the most common types of artificial neural networks (ANNs). The FNN has a multilayer structure consisting of input, hidden, and output layers. Data flows through the network in a single direction—from input to output—without any feedback or loops. This model is best suited for cases involving relatively simple datasets, independent variables, and fewer random factors. It is simple and effective for problems where the data do not involve sequential or temporal dependencies. Applications of this model in wave forecasting and marine climate conditions have been reported by several authors [8], [9], [6]. Due to its simplicity and speed, this model is among the most widely used approaches for forecasting marine climate parameters and conditions [10].

2.2. Convolutional Neural Network (CNN)

CNNs consist of convolutional layers that apply convolution operations to the input data. These layers enable the system to build hierarchical representations of features. This model is primarily used for image processing and spatial data tasks (e.g., weather images and videos). Through this approach, CNNs have been applied to forecast wave height and direction [11], [12].

2.3. Recurrent Neural Network (RNN)

RNNs are designed so that the output information is fed back as input data, and continues to be processed until the errors reach a target value. RNNs perform well in tasks where later data points depend on earlier ones in a given sequence. Therefore, the model is suitable for time-dependent variables [13], [14], [15].

2.4. Long Short-Term Memory (LSTM)

LSTM is a special type of RNN designed to overcome the problem of gradient vanishing, which slows down the learning process and biases the model toward more recent inputs while "forgetting" earlier information—a common limitation of traditional RNNs when analyzing large time-series datasets.

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LSTM networks are capable of retaining long-term information and predicting complex temporal fluctuations of variables. Consequently, this model has been increasingly applied in recent years, particularly in short-term wave forecasting [16], [17], [18], [19].

2.5. Hybrid Models (HM)

Hybrid models (HM) combine mathematical or physical models with deep learning approaches. They leverage the strengths of both methods to improve the accuracy of wave forecasting. For example, the output from a physical model can be used as input to a deep learning network to refine predictions. Some representative hybrid approaches include:

- Combination of ANN with wavelet analysis (WNN) [20], [21], [22];

- Combination of fuzzy logic and ANN [23], [24], [25];

- Integrated models using orthogonal function-based approaches (EOFWNN) [5].

3. Assessment of ship manoeuvrability operability and navigational Risks

3.1. Overview

Whether a vessel can be maneuvered into a channel largely depends on natural conditions, among which waves play an almost decisive role. Calculating and forecasting ship motions in waves and thereby determining the under-keel clearance before entering a channel-has attracted considerable attention. Accurate forecasting of ship motions under wave action not only enhances the efficiency of channel utilization but also minimizes navigational risks.

There are several approaches to determining and predicting ship motions in waves. A linear regression model between the incident wave spectrum and the ship motion spectrum was proposed by Savenije [26]. This model was incorporated into a software program called HARAP [27], which became an integral component of the real-time ship-operability risk forecasting system applied to the Rotterdam channel [26]. Following a similar approach, PIANC [28] suggested calculating under-keel clearance using the significant wave height. An experimental model for container ships to determine the probability of seabed contact was developed by USACE [29]. However, applying linear models to represent the relationship between waves and ship motions has proven to be unreliable [30].

A significant contribution to improving ship motion forecasting models and under-keel clearance calculations was made by Ohtsu and colleagues [31]. This model is currently applied in the Japanese Port Design Standards [32]. To establish the relationship between wave parameters and ship motions, numerous experimental studies combined with numerical simulations have been conducted. Some mathematical functions describing this relationship have been developed and presented in the form of charts. However, these experiments have generally been limited to certain ship types.

The application of AI models to forecast ship motions in waves has received increasing attention. Machine learning models have been used to predict ship trajectories under real operating conditions [33]. The research results provide a basis for estimating the probability distribution of dynamic ship characteristics (such as speed, yaw, drift angle, and surge acceleration) as well as the risk of grounding along selected routes. LSTM [34] and RNN [35] models have also been applied, in combination with wave and ship motion survey data collected simultaneously, to calibrate and validate ship motion forecasting models. Nevertheless, most of these studies have been conducted in deep-water environments. Scenarios related to ship-operating conditions (such as vessel speed and draft) in shallow waters have not yet been sufficiently addressed. Moreover, the greatest drawback of this research direction is that it requires an extensive volume of survey and measurement data to develop highly reliable and accurate models something that is not always feasible.

3.2. Transfer function (RAO) parametric model

To overcome the aforementioned limitations, this paper proposes developing the ship motion transfer function using a parametric model combined with field surveys for model validation. To construct the transfer function, the numerical ship-motion model SEAWAY [36] is employed. Under this approach, most ship-operating scenarios in shallow waters are considered. Finally, AI tools are applied to generalize the transfer function and to compute ship motions under wave conditions forecasted in advance. The sequence of steps for constructing the transfer function and forecasting ship motions is illustrated in Figure 3.

The basic formula for determining the transfer function, H(ωe), based on the ship motion spectrum and the wave spectrum, is expressed as follows [30]:

$$|H(\omega_e)|^2 = \frac{S_r(\omega_e)}{S_\eta(\omega_e)} \quad (1)$$

where:

ω_e is the encounter wave frequency,

S_r is the ship motion spectrum,

S_η is the incident wave spectrum.

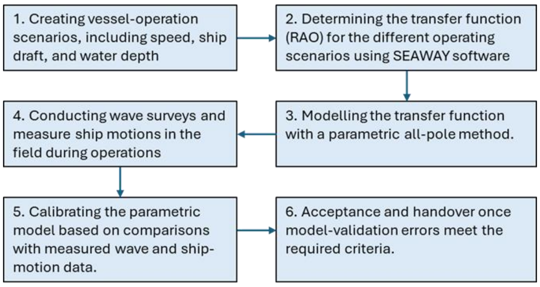

Figure 3. Flowchart for developing the ship motion forecasting model

For each operating scenario in shallow waters including ship speed, under-keel clearance, and wave parameters of equation (1) can be expressed in the following form [30]:

$$H(s) = \frac{b(0)+b(1)s^{-1}+\cdots+b(n)s^{-n}}{1+a(1)s^{-1}+\cdots+a(m)s^{-m}} = \frac{\sum_{k=0}^{n} b(k)s^{-k}}{1+\sum_{k=1}^{m} a(k)s^{-k}} \quad (2)$$

Here, *s* is the angular frequency vector at which the transfer function *H*(*s*) is defined by the numerator and denominator polynomials (real or complex), represented by the vectors *b* and *a*, respectively. Once *H*(*s*) and *s* are known, nonlinear optimization to determine a(k) and b(k) is typically carried out using Prony's or Shank's algorithms, both of which are available in the MATLAB Signal Processing Toolbox. For the present problem, equation (2) can be rewritten as follows:

$$H(\omega_e \mid V, kc) = \frac{\sum_{k=0}^{n} b(k|V,kc)\omega_e^{-k}}{1+\sum_{k=1}^{m} a(k|V,kc)\omega_e^{-k}} \quad (3)$$

The coefficients a(k) and b(k) are defined as polynomial functions of V and kc as follows:

$$a(k \mid V, kc) = \sum_{j=1}^{p+1}\left[\sum_{i=1}^{q+1} \theta_{i,j} V^{q+1-i}\right] kc^{p+1-j};\ k = 1 \div m$$

$$b(k \mid V, kc) = \sum_{j=1}^{p+1}\left[\sum_{i=1}^{q} \phi_{i,j} V^{q+1-i}\right] kc^{p+1-j};\ k = 0 \div n$$

(4)

To construct the transfer function *H(ωe)* for different ship-operating scenarios, the parameters *a* and *b* in equation (3) must be determined, which correspond to the coefficients θ and ϕ in equations (4). The estimation of these model parameters can be carried out either from measurement data collected during port operations or by employing numerical ship-motion models. The detailed content of this part will be presented in subsequent publications.

3.3. Model for determining the probability of ship-bottom interaction induced by waves

Using the wave-forecasting results, the probabilistic model can be applied to determine the likelihood of ship-bottom interaction with the channel bed for a given manoeuvring scenario.

Vessel motions under wave action constitute a random process in which the amplitude and period of motion depend on the incident wave parameters (wave height, wave period, and wave direction). Let $x(t)$denote the vertical motion at the lowest point of the ship's hull over a time interval T_h. The probability that the motion x(in meters) exceeds a critical limit β within the interval T_h is denoted as α, and this relationship can be expressed using the Poisson probability function as follows [30]:

$$\beta = \sqrt{m_0}\left[-2\ln\left(-\ln(1-\alpha)/\left(\frac{T_h^2}{2\pi}\sqrt{\frac{m_2}{m_0}}\right)\right)\right]^{\frac{1}{2}} \quad (5)$$

In which *m₀* and *m₂* are the zeroth-order and second-order moments of the ship motions, determined as follows:

$$\boldsymbol{m_o} = \int_0^\infty \boldsymbol{S_r}(\boldsymbol{w_e})\boldsymbol{dw_e}$$

$$m_2 = \int_0^\infty w_e^2 S_r(w_e)dw_e \quad (6)$$

Currently, many numerical models have been developed based on the strip theory to determine a ship's motion parameters, including the ship motion spectrum, as well as the amplitudes and periods of its motions [36].

4. Application to the Quang Ninh Sea Area

4.1. Data Collection

Wave and wind data for the offshore area of Quang Ninh (coordinates: 108.5°E; 21.0°N) were collected from the National Oceanic and Atmospheric Administration (NOAA). The dataset includes wind speed and direction, as well as wave height, direction, and period. The collection period spans from 2018 to 2023. An excerpt of this dataset is presented in Table 3, which was used for constructing the ANN models.

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Table 3. Extract of NOAA data used for developing ANN models

The coordinates of the point extracted from NOAA (108.5°E; 21.0°N)					
Time	**Wind speed** (m/s)	**Wind dir.** (°)	**Hs** (m)	**Tp** (s)	**Wave dir.** (°)
2018-01-01 0:00	7.697077367	43.21008939	0.76	3.51	36.72
2018-01-01 3:00	7.721580149	48.46505515	0.81	3.74	38.47
2018-01-01 6:00	6.071704868	58.19467108	0.75	3.77	41.57
2018-01-01 9:00	4.871765594	61.96210361	0.6	3.67	48.26
2018-01-01 12:00	4.682445942	102.5818962	0.52	3.43	71.8
2018-01-01 15:00	5.958867342	119.2320477	0.6	3.9	111.64

4.2. Data Analysis and Normalization

The formula for normalizing the input matrix data and the target vector is as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{7}$$

In which, x is the original data; x' is the normalized data; x_{max}, x_{min} are the maximum and minimum values of the input data.

4.3. Model Selection

Due to the limitations discussed above regarding the application of RNN and CNN models for long time-series data, only three models-FNN, LSTM, and the hybrid CNN-LSTM-were tested and compared in this study.

4.4. Model Training and Development

Model development and training were conducted

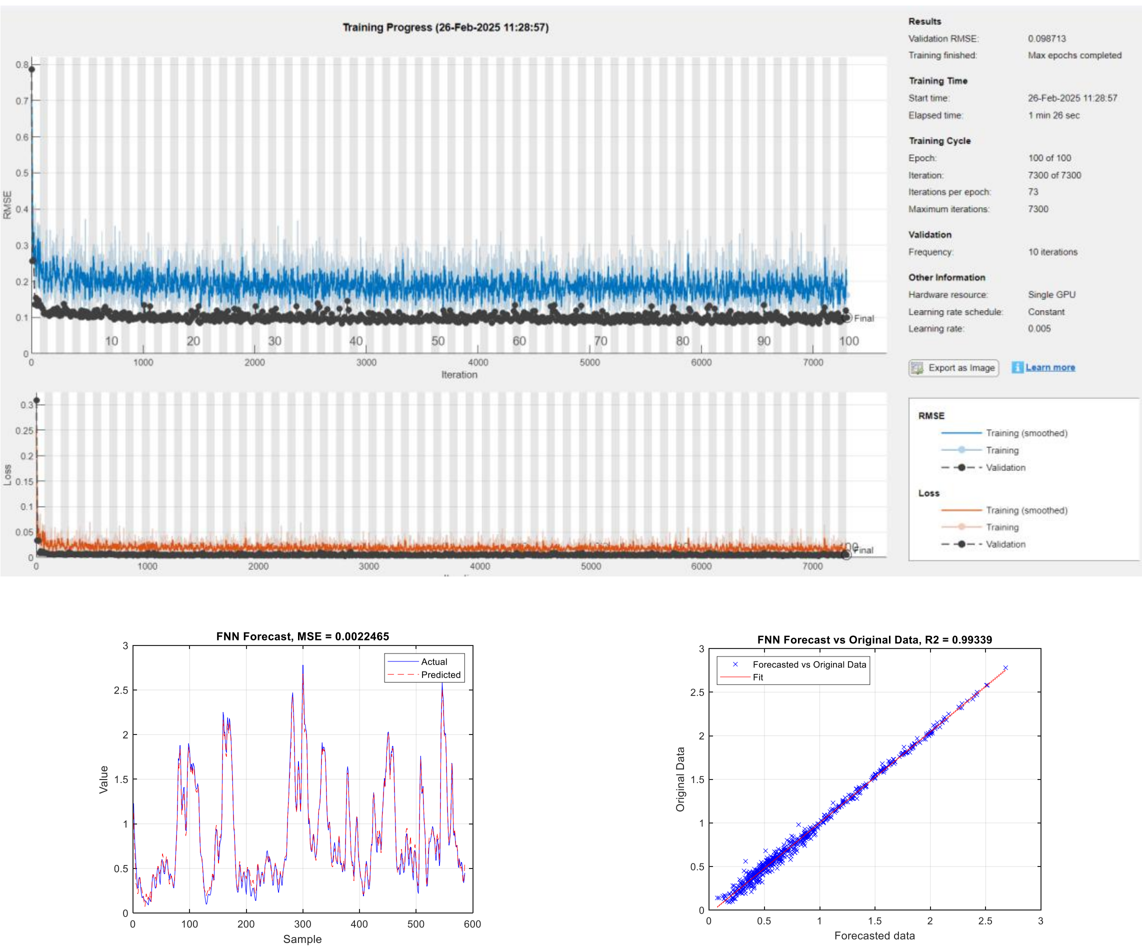

Figure 4. Training results (top) and model validation (bottom) for the FNN model

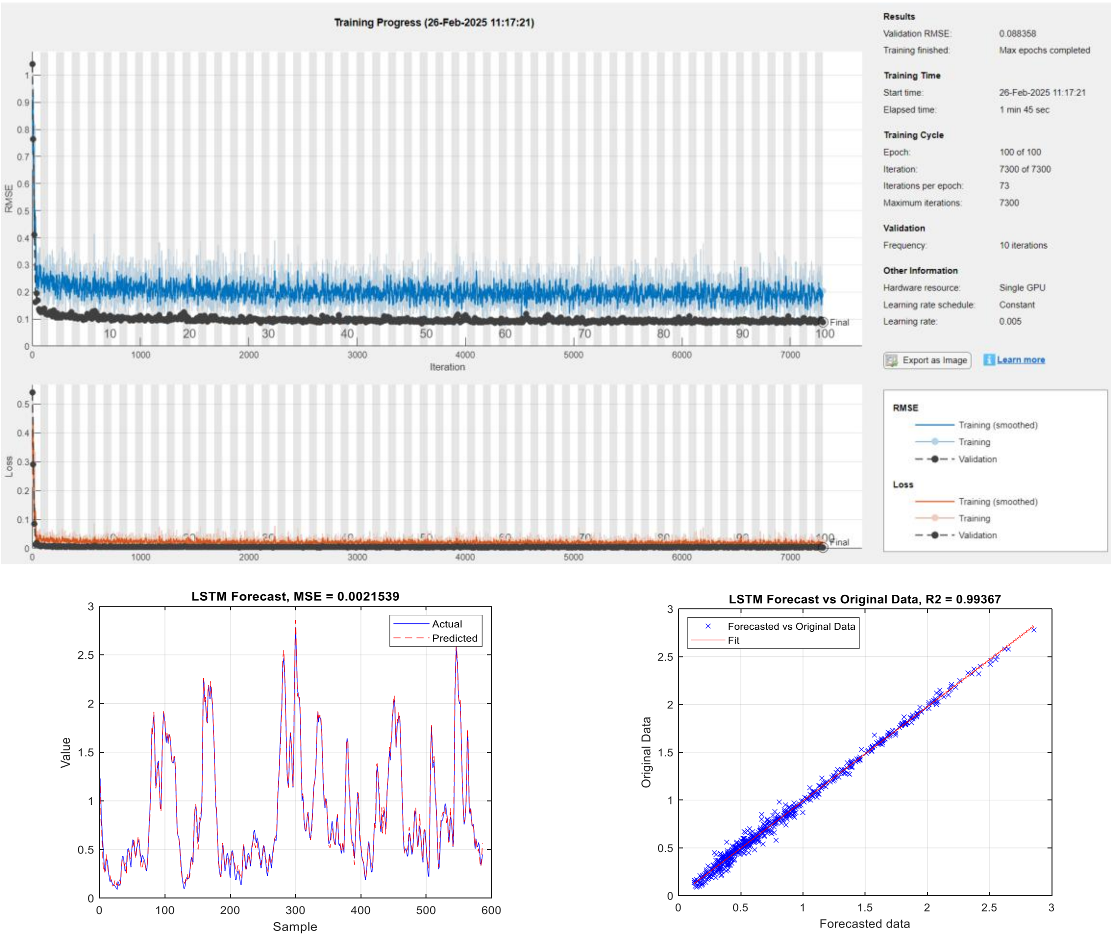

Figure 5. Training results (top) and model validation (bottom) for the LSTM Model

on 80% of the collected data, while the remaining 20% was used for model validation. The mean squared error (MSE) regression function was employed to measure the deviation between the calculated results (predicted wave height, direction, or period) and the actual data. The entire process was implemented using the ANNs functions in Matlab R2023b. The training and validation results of the models are presented in Figures 4, 5, and 6.

These figures shows the Root Mean Square Error (RMSE) for both training and validation data across 1,000 iterations. The blue curve (training RMSE) and black curve (validation RMSE) fluctuate within a narrow numerical range, indicating stable error values, no divergence between training and validation, no overfitting.

The RMSE values quickly decrease early in training and then stabilize around a consistent band (e.g., approximately X-Y units, depending on the scale in the figures).

The orange curve (training) and grey curve (validation) converge rapidly toward a small constant value. The numerical scale of Loss remains nearly flat across the last ~80% of iterations.

The right-hand "Results" panel shows the number of epochs completed, e.g., 200 epochs. Number of iterations: 7,300. These values indicate the model required only a portion of the full training duration to reach its error plateau; additional epoch cycles would not improve accuracy, as seen from numerical stabilization of RMSE and Loss.

It can be concluded that both training and validation RMSE decrease rapidly and then stabilize, confirming that the selected number of epochs is sufficient for model convergence. The close tracking of training and validation curves demonstrates that the chosen network size (with ten of neurons and hidden layers) is appropriate, with no signs of overfitting. The stable oscillation patterns in the RMSE and Loss curves further indicate that the learning rate and batch size support stable optimization. The observed performance plateau suggests that increasing the

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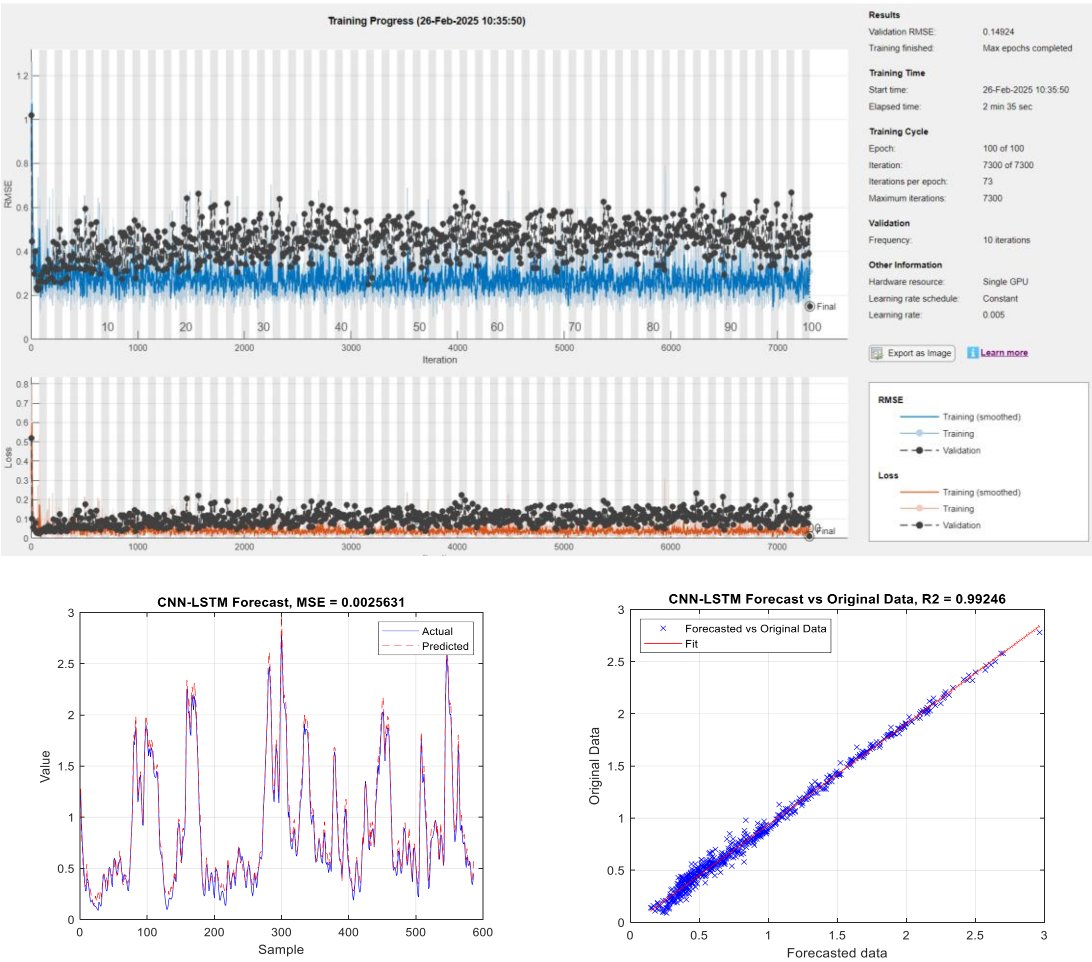

Figure 6. Training results (top) and model validation (bottom) for the CNN-LSTM model

model size or training duration would not improve accuracy. Therefore, the adopted hyperparameters represent an optimal trade-off between model complexity, computational efficiency, and predictive performance.

4.5. Forecasting and Verification

After the network was trained and the model constructed, forecasting was performed using real-time data. The predicted data must continue to be verified against actual measured data in order to improve the model. Due to limited funding, this stage will be carried out in the next phase of the research.

4.6. Analysis and Evaluation

The comparative calculation results in Table 4 show that the LSTM network provides the highest accuracy, followed by FNN and CNN-LSTM. In terms of training time, FNN is the fastest, followed by LSTM and then CNN-LSTM.

The superior accuracy of LSTM over CNN-LSTM can be explained by the fact that, for purely time-series forecasting tasks such as ocean wave conditions, LSTM has an outstanding ability to retain and learn

Table 4. Results comparison

Criteria	FNN	LSTM	CNN-LSTM
Training time	1 minute and 26 seconds	1 minute and 45 seconds	2 minutes and 35 seconds
Validation RMSE (after training)	RMSE=0.098713	RMSE=0.088358	RMSE=0.14924

from correlations between current and past data over the long term without being affected by convolutional layers. However, if spatial features play an important role (e.g., wave height maps, seabed topography, or low-pressure systems stored in image form), CNN-LSTM could be a better choice.

As expected, compared to FNN, LSTM often outperforms in forecasting tasks because it can effectively learn temporal relationships, adapt to non-stationary data, and handle long-term time series. However, if the task requires processing short-term, sequential, and stable data, FNN may be a simpler option with faster training time.

5. Conclusion and Recommendations

This paper compares several ANN models and analyzes the scope of application of each model in short-term wave forecasting for port and maritime channel operations. The results show that wave forecasting using AI models achieves high accuracy, faster computation time, and lower cost compared to numerical models. The comparison indicates that the LSTM network yields the highest accuracy in cases where the collected data are numerical time series over the long term. In contrast, for hydro-meteorological data in the form of satellite imagery, the CNN-LSTM model may provide higher accuracy.

The proposed direction for future research is to analyze and compare ANN models in extending the forecasted wave height and period after obtaining results from the LSTM network. At the same time, based on the forecasting results, the study will analyze and assess ship operability and develop the safest and most efficient maneuvering plans.

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Declaration:

The author declares that this paper is the result of her own research, has not been published previously, is not plagiarized or copied, and there are no conflicts of interest among the authors.

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