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An Optimized Port Operation Efficiency Prediction Model Based on ESN and LSTM

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Abstract

With the in-depth digital transformation of the global shipping industry, the accurate prediction of smart port operation efficiency has become a key factor in enhancing the competitiveness of international supply chains. Aiming at the limitations of traditional models in handling nonlinear dynamics and noisy multi-scale data in port operations, this paper proposes a dual-model optimization framework based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Echo State Network (ESN), and Bidirectional Attention-Enhanced Long Short-Term Memory Network (Bi-ALSTM). At the macro level, CEEMDAN is used to decompose the multi-scale features of port efficiency signals, and a lightweight prediction model is constructed in combination with ESN. At the micro level, a bidirectional attention mechanism is introduced to improve LSTM, enhancing the ability to model temporal dependencies. Experimental results show that the training time of CEEMDAN-ESN is only 0.35 seconds, demonstrating a significant real-time advantage; the Mean Absolute Error (MAE) and Mean Squared Error (MSE) of Bi-ALSTM on the test set are 123.47 and 25475.36, respectively, which are 18.10% and 30.50% higher than those of the traditional Recurrent Neural Network (RNN) model. These results verify the comprehensive advantages of the proposed models in terms of accuracy and efficiency. This study provides an interpretable quantitative tool for dynamic scheduling and risk early warning of smart ports, and helps transform port management towards an automated and predictive model.

Keywords

Port Operation Efficiency Prediction, ESN, LSTM, CEEMDAN, Attention Mechanism Classification

1. Introduction

In recent years, the global shipping industry has undergone a profound digital transformation, and smart port initiatives have become the cornerstone of modern logistics and trade. As a crucial hub in the international supply chain, port operation efficiency directly affects throughput, costs, and competitiveness. In response to the call of the Ministry of Transport for expanding technological innovation platforms, and under the guidance of national strategies such as the Outline for Building a Transport Power, Guiding Opinions on the Development of Intelligent Shipping, and the 14th Five-Year Plan for Digital Transportation Development, there is an urgent need to apply advanced data-driven methods throughout the entire life cycle of ships. By leveraging spatiotemporal feature extraction and intelligent algorithms, it is expected to transform the traditional experience-driven port management into a predictive, automated, and highly resilient ecosystem.

Despite the increasing popularity of port automation and sensor networks, existing efficiency evaluation and prediction models often adopt static or linear assumptions, making it difficult to capture the inherent nonlinear characteristics and complex dynamics of port operations. Traditional time-series methods have limited capabilities in handling noisy multi-scale signals and usually fail to integrate heterogeneous historical and real-time data streams.

To bridge this gap, this paper proposes improved methods for two models, namely the Long Short-Term Memory (LSTM) network architecture and the Echo State Network (ESN). By introducing mechanisms such as the Bidirectional Attention-Enhanced Long Short-Term Memory Network (Bi-ALSTM) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), the study aims to extract rich spatiotemporal features, improve prediction accuracy and training speed, and enhance the generalization ability of the models. This enables real-time efficiency evaluation, dynamic early warning of key performance indicators, and provides reliable decision support for the operation of next-generation smart ports.

2. Port Operation Efficiency Prediction Models

2.1. Definition of Port Operation Efficiency

Port efficiency refers to the comprehensive operational effectiveness of a port in cargo and ship operations, evaluated based on multi-dimensional core operational data including daily cargo handling volume, daily berthing duration, daily anchoring duration, and daily number of ships handled. Ship-related operational indicators (e.g., daily berthing/anchoring duration) are closely linked to port efficiency, and their accuracy directly affects prediction reliability. Yoon *et al.* similarly emphasized the importance of ship trajectory data in maritime operation optimization—they used AIS (Automatic Identification System) data to model vessel voyage routes and improve arrival time prediction accuracy [1]. In our study, while we focus on port efficiency rather than vessel ETA, the logic of leveraging ship operational data to reflect system dynamics aligns with their research, further validating the rationality of selecting "daily number of ships handled" and "berthing duration" as core features.

Such a set of indicators reflects the dynamic coupling relationship between cargo throughput efficiency, ship stay time, and operation scheduling. Meanwhile, port efficiency is indirectly affected by weather conditions (e.g., wind speed, temperature) that regulate ship berthing/anchoring duration. This definition emphasizes the collaborative analysis of multi-dimensional data, aiming to explore efficiency bottlenecks in port operation processes by mining the temporal correlation features of "cargo handling—ship stay", and further provides a quantitative basis for optimizing berth scheduling and refining resource allocation.

The port efficiency in this paper is calculated using the following formula: Port Efficiency = Daily Cargo Handling Volume/Daily Berthing Duration.

Among them, the daily cargo handling volume adopts the Net Tonnage (NET) of ships, which refers to the operational volume obtained by subtracting non-operational volume from the total tonnage of a ship. This differs from the commonly used Deadweight Tonnage (DWT)—the total weight of cargo, fuel, fresh water, crew, luggage, and other consumables that a ship can carry in a fully loaded state. The selection of NET has two significant advantages: first, it eliminates the interference of non-cargo load factors; second, it aligns with actual port operations where the number of containers (rather than weight) is the primary handling indicator.

The empirical analysis in this study relies on two complementary datasets for the Port of New York:

Maritime operational data: Provided by COSCO Shipping Technology, it contains 10,227 records across 131 columns, covering detailed information including anchoring, waiting, and berthing durations, daily number of ships handled, ship Net Tonnage (NET), and vessel characteristics (e.g., length, width). This dataset spans from January 3, 2021, to October 10, 2024, with a fixed 6-hour sampling frequency.

Weather data: Sourced from the Local Climatological Data (LCD) of the U.S. National Centers for Environmental Information (NCEI), it focuses on wind speed and temperature. To ensure spatial relevance to the port, data from the observation point closest to the Port of New York is selected, with an hourly update frequency.

This combination of multi-source, fine-grained datasets not only ensures the reliability of port efficiency measurement and the robustness of subsequent modeling but also supports the representativeness of research findings and the reproducibility of experimental procedures.

2.2. CEEMDAN-ESN

In the fields of signal processing and time-series analysis, CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) and ESN (Echo

State Network) each demonstrate strong performance. The model constructed by combining CEEMDAN and ESN can effectively integrate the advantages of both, providing a more efficient solution for the analysis and prediction of complex non-stationary signals.

2.2.1. CEEMDAN

As an advanced signal decomposition method, CEEMDAN aims to overcome the limitations of the traditional Empirical Mode Decomposition (EMD) and its variants (e.g., EEMD, Ensemble Empirical Mode Decomposition). By adaptively adding noise to the original signal and performing multiple ensemble averaging operations, it decomposes the complex non-stationary signal into a series of Intrinsic Mode Functions (IMFs) with different characteristic scales. These IMF components range from high frequency to low frequency, respectively representing the oscillation characteristics of the original signal at different scales, thereby fully excavating and separating the hidden information in the original signal. The decomposition formula is as follows:

$$x(t) = \sum_{k=1}^{n} IMF_k(t) + residual(t)$$

After decomposition, the dataset used in this paper yields a total of 8 IMFs and one residual term, as shown in **Figure 1** below:

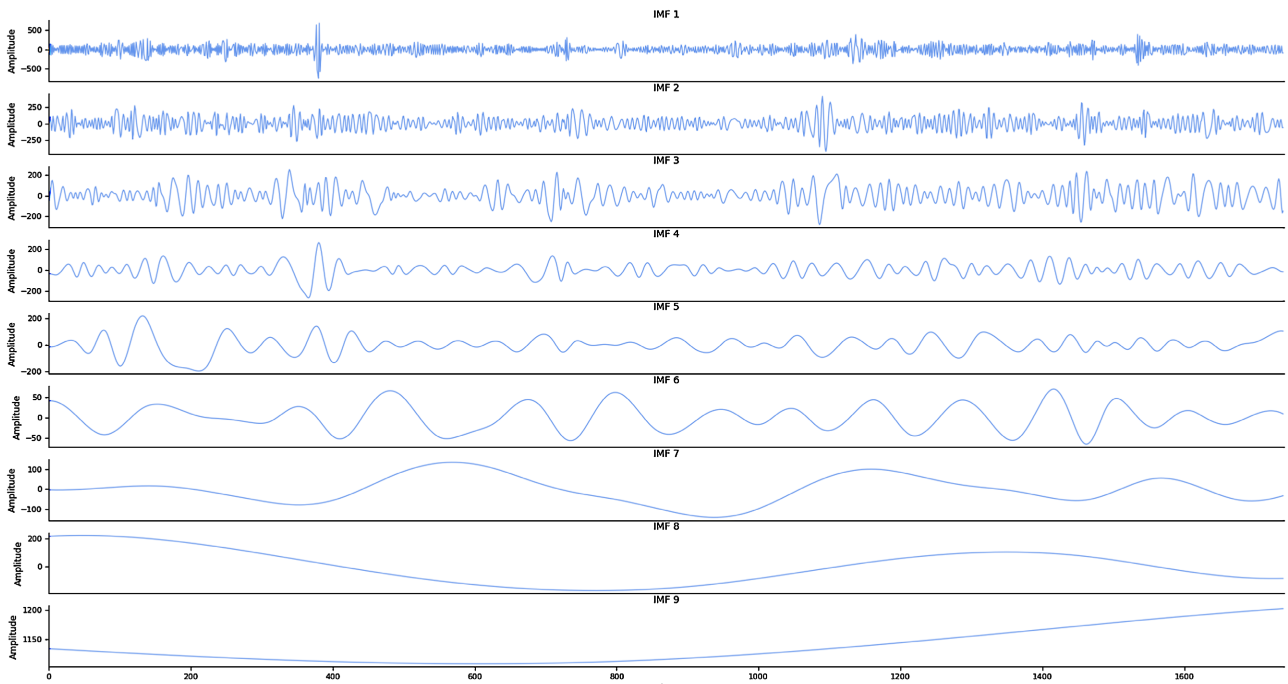

Figure 1. Results of CEEMDAN decomposition.

2.2.2. ESN

The Echo State Network (ESN), proposed by Jaeger and Haas in 2004 [2], is a special type of Recurrent Neural Network (RNN). It is designed to efficiently process time-series data while avoiding the complex training process of traditional

RNNs. Unlike traditional neural networks that require gradient-based optimization for all parameters, ESN adopts a fixed random reservoir and combines it with a simple linear regression training method, making it particularly effective in time-series prediction and nonlinear system modeling.

The core innovation of ESN lies in its three-layer architecture, as shown in Figure 2:

An input layer that receives external signals;

A dynamic reservoir layer with sparse random connections;

A linear output layer.

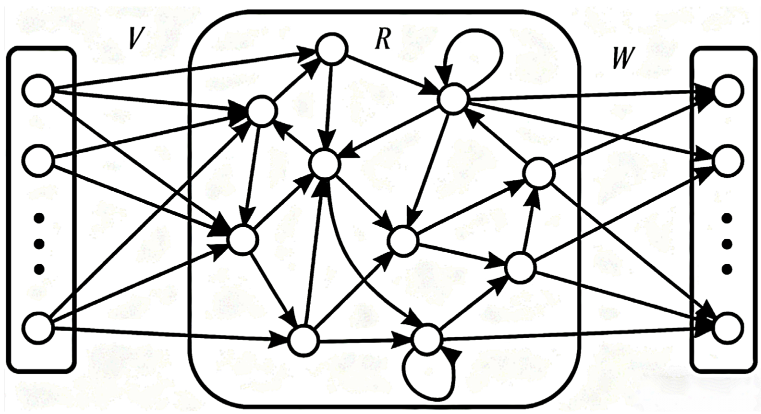

Figure 2. Structure diagram of ESN.

The reservoir (denoted by "R") contains hundreds of randomly connected neurons, and its weights remain unchanged during the training process. This reservoir nonlinearly maps the input signal to a high-dimensional space, generating rich temporal feature representations, which can then be linearly decoded by the output layer. The update formula is as follows:

$$x(t) = \tanh\left(W_{res}x(t-1) + W_{in}u(t) + W_{feedb}y(t-1)\right) + n$$

2.2.3. Model Construction

1) Signal Decomposition and Feature Input

The CEEMDAN algorithm is used to perform multi-scale decomposition on the port efficiency signal (daily net tonnage/daily berthing duration), resulting in 8 Intrinsic Mode Functions (IMFs) and 1 residual term (as shown in Figure 1). Each IMF component corresponds to the oscillation characteristics of the original signal from high frequency to low frequency, effectively separating noise interference and trend terms.

2) Model Implementation

The model is developed based on the Python 3.8 platform, and the core algorithm is implemented relying only on the Numpy library.

3) Model Training and Strategy

In terms of data division, the time-series data is divided into a training set and a test set in a 7:3 ratio while maintaining the time sequence, so as to preserve the temporal dependency of the data. In terms of model construction, as shown in the figure below, independent ESN sub-models are established for the 9 signal components obtained from decomposition. Each sub-model shares 6-dimensional input features (daily net tonnage, daily berthing duration, daily anchoring duration, daily number of ships handled, wind speed, temperature), and the final prediction result is composed of the sum of the outputs of each sub-model. These six features were selected because they capture both the operational dynamics of cargo handling and the external environmental influences on port efficiency; however, certain potentially influential factors, such as tidal conditions or crane availability, are not included due to data limitations, which may introduce a degree of modeling bias. The structure is shown in Figure 3.

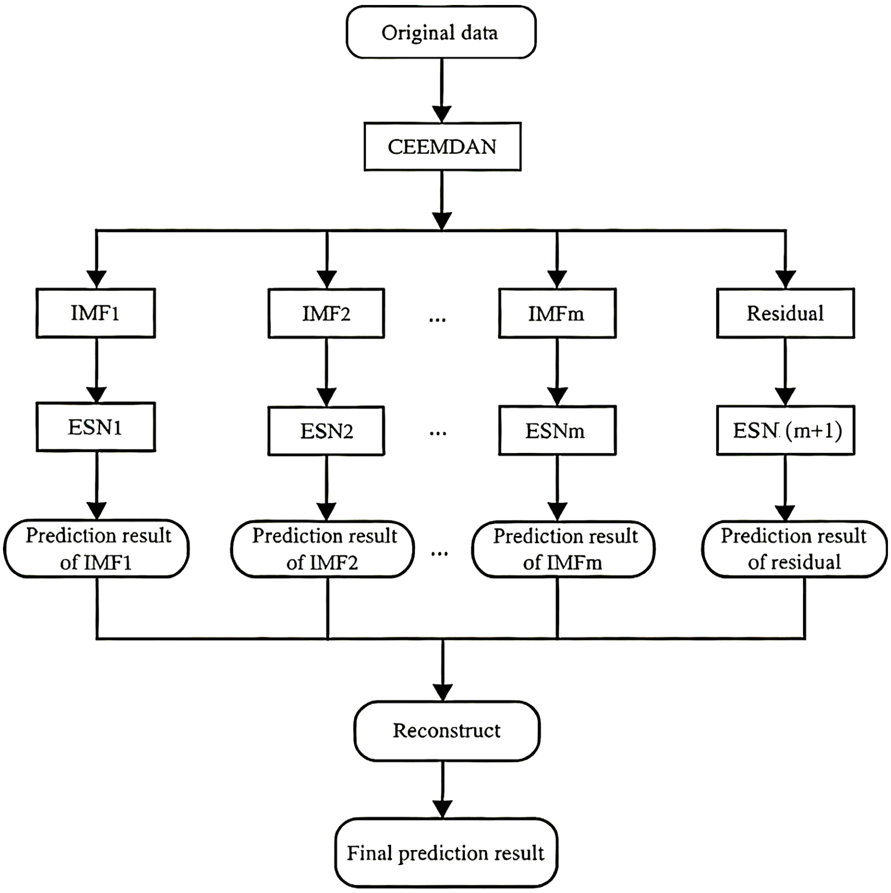

Figure 3. Structure of CEEMDAN-ESN.

The key hyperparameters for CEEMDAN decomposition and ESN modeling, determined through experimental tuning to balance performance and computational efficiency, are listed in Table 1.

2.3. Bi-ALSTM

2.3.1. LSTM

The Long Short-Term Memory (LSTM) model is a special branch of Recurrent

Neural Networks (RNNs), proposed by Hochreiter and Schmidhuber in 1997 [3]. For a long time, LSTM has been widely used in natural language processing, time-series prediction, and speech recognition for sequential audio signal processing. Its structure is shown in **Figure 4** and the formulas are as follows.

Table 1. Parameters of CEEMDAN and ESN.

Category	Parameter	Value
CEEMDAN Settings	Number of Ensembles (trials)	100
	Noise Amplitude	0.01
ESN Hyper-parameters	Reservoir Size	12
	Spectral Radius	0.5
	Sparsity	0.5

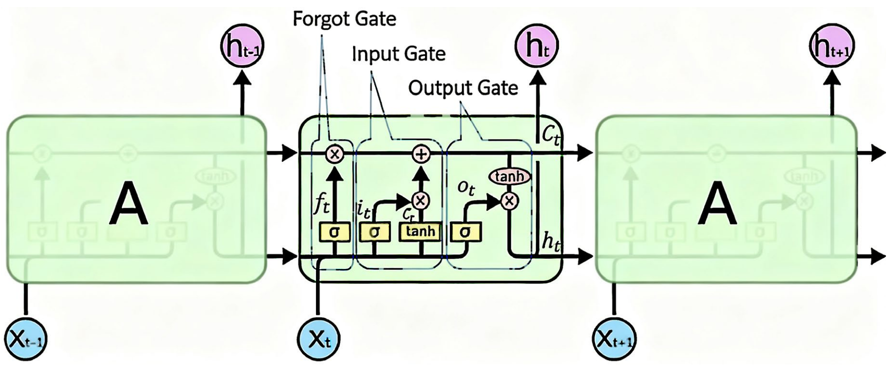

Figure 4. Structure diagram of LSTM.

$$\begin{array}{ll} \text{Forget Gate} & f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \\ \text{Input Gate} & i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \\ \text{Candidate} & \tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \\ \text{Memory} & C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\ \text{Output Gate} & o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \\ \text{Hidden} & h_t = o_t \odot \tanh\left(C_t\right) \end{array}$$

where:

(σ) represents the sigmoid activation function (S-shaped function).

($\odot$) denotes element-wise multiplication (Hadamard product).

((W_*)) and ((b_*)) represents the trainable weight matrices and bias vectors respectively.

([h_{t-1}, x_t]) represents the vector concatenation operation.

The core advantage of LSTM's gate structure lies in its ability to address the long-term dependency problem of traditional RNNs, as elaborated by Olah [4] in his classic analysis of LSTM networks. He emphasized that the forget gate, input gate, and output gate work in synergy to regulate information flow in the cell state—similar to a "conveyor belt" that retains critical temporal features while discarding redundant noise. This mechanism is particularly vital for port efficiency prediction, where historical data (e.g., berthing duration of the past 72 hours) has a significant impact on future efficiency trends.

2.3.2. Model Optimization

To further improve the prediction accuracy, this study also introduces the Attention Mechanism and the Bidirectional Mechanism. A study by Kumar and Singh in 2023 pointed out that, fundamentally, the attention mechanism is a memory mechanism that explores key features by selectively extracting time-series inputs, facilitating the overall representation of data dynamics [5]. Its core goal is to use the attention distribution and learnable weights to independently determine which parts of the input are more important. For the bidirectional mechanism, the Bidirectional Long Short-Term Memory Network (BiLSTM) architecture integrates two independent LSTM layers to process sequences in opposite time directions (forward: past → future; backward: future → past), thereby achieving comprehensive modeling of temporal dependencies. Compared with the traditional unidirectional LSTM that only relies on historical context, the bidirectional processing of Bi-LSTM can enhance pattern recognition capabilities by fusing sequence information from the past and the future. The LSTM structure adopted in this paper is shown in Figure 5 below.

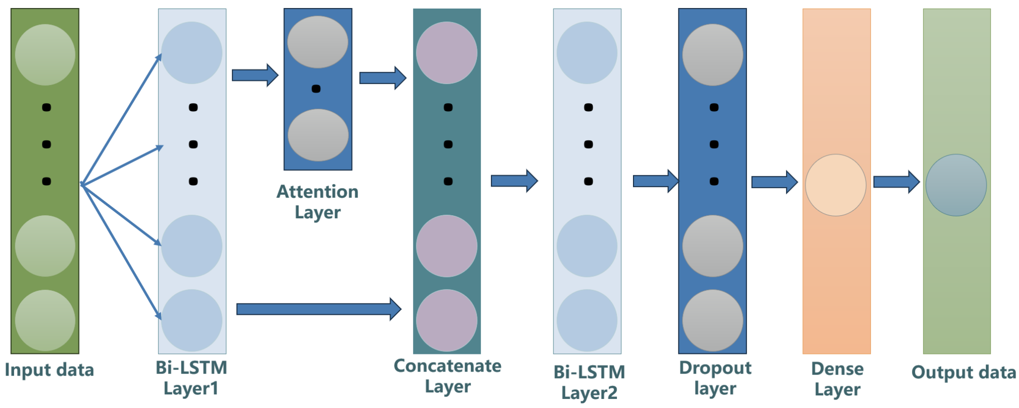

Figure 5. Structure diagram of Bi-ALSTM.

2.3.3. Model Construction

1) Feature Input

A total of 6 features—daily net tonnage, daily berthing duration, daily anchoring duration, daily number of ships handled, wind speed, and temperature—are selected as inputs: the latter two (wind speed, temperature) are derived from Local Climatological Data (LCD) of the U.S. National Centers for Environmental Information (NCEI, 2020.01-2024.10), with data from the observation point closest to the port carefully selected; all 6 features cover core port operation dimensions and reflect the dynamic correlation between cargo handling efficiency and ship stay time. Notably, critical variables are excluded due to data unavailability: tide levels (impacting berthing accessibility and vessel water depth requirements) are left out because the NCEI LCD weather data lacks specialized hydrological data for tide analysis (e.g., tide height, tidal cycle); crane availability (a core factor restricting cargo handling speed) is not included as the Port of New York maritime operational dataset (provided by COSCO Shipping Technology) has no real-time crane status logs (e.g., working hours, fault records).

Subsequently, time-series data are generated based on the preprocessed data, and the time axis is divided into short data sequences according to the hyperparameter sequence length using a sliding window algorithm. For example, if the original data is (([X_1, X_2, X_3, X_4, X_5, X_6])) and the sequence length is 3, the input feature X is converted into a two-dimensional list (([[X_1, X_2, X_3], [X_2, X_3, X_4], [X_3, X_4, X_5]])), and the corresponding target value y is (([Eff_4, Eff_5, Eff_6])), so as to preserve the temporal dependency of the data.

2) Model Implementation

The Bi-ALSTM model is constructed based on Tensorflow (2.19.0) framework. As shown in **Figure 5**, it consists of 7 layers in total:

Input Layer: Receives the original sequence data, with a dimension of (sequence length, number of features).

Bidirectional LSTM Layer: Performs bidirectional processing of the sequence for the first time, retains complete time-step information through return_sequences = True, and captures temporal dependencies in the forward (past → future) and backward (future → past) directions.

Time-Step Attention Layer: Dynamically calculates the importance weights of each time step to enhance key temporal features.

Concatenation Layer: Fuses the output of the bidirectional LSTM with the attention-weighted features along the channel dimension to construct an enhanced temporal representation.

Second Bidirectional LSTM Layer: Sets return_sequences = False to retain only the final hidden state and extract high-level temporal patterns from the fused features.

Dropout Layer: Randomly deactivates neurons during training to suppress overfitting.

Fully Connected Layer: Maps high-level representations to regression prediction values and outputs the port efficiency prediction results.

Through attention-driven feature optimization, bidirectional temporal modeling, and multi-source feature fusion, this architecture realizes end-to-end learning from the original sequence to the target value.

3) Model Training and Strategy

Dataset Division: The first 70% of the data is divided into the training set and the remaining 30% into the test set in chronological order to ensure that the temporal logic is not disrupted.

Optimizer Configuration: The Adam optimizer is adopted, the learning rate is determined through hyperparameter tuning, and gradient clipping is introduced to suppress gradient explosion and improve training stability.

Overfitting Control: The early stopping mechanism is enabled, with patience = 8 (training stops if there is no improvement for 8 epochs) and delta = 1e−5 (minimum improvement threshold).

Training Parameters: To fully explore the potential of the model, a genetic algorithm is used to optimize the hyperparameters in the model, including Units, Batch_size, Learning_rate, Sequence_length, and Dropout_rate, realizing systematic exploration of the high-dimensional parameter space.

3. Results and Analysis

As shown in Figure 6 and Figure 7, both models can well predict the trend of port efficiency and fit the real values, but they are unable to predict some of the extremely large or small values that exceed expectations. It is obvious that the prediction capabilities of both models are excellent and their effects are similar.

Next, the accuracy and efficiency of the models will be analyzed from a numerical perspective, covering four dimensions: model training time, test set MAE, test set MSE, and the degree of improvement of MAE and MSE compared with RNN.

From Table 2, it can be seen that CEEMDAN-ESN has a training time of only 0.35 seconds, significantly lower than RNN (4.86 seconds) and Bi-ALSTM (30.07 seconds). Bi-ALSTM performs best in test set MAE (123.47) and MSE (25,475.36), which are 18.10% and 30.5% lower than RNN, and 2.4% and 7.0% lower than CEEMDAN-ESN, respectively. Notably, ARIMA (MAE = 171.34, MSE = 45,877.36) performs the worst, consistent with Ning *et al.*'s findings [6]—they compared ARIMA, LSTM and Prophet in oil production time-series forecasting and pointed out that traditional statistical models like ARIMA struggle to capture nonlinear dependencies and multi-scale fluctuations in sequential data. This limitation is more obvious in port operations (affected by cargo throughput, ship

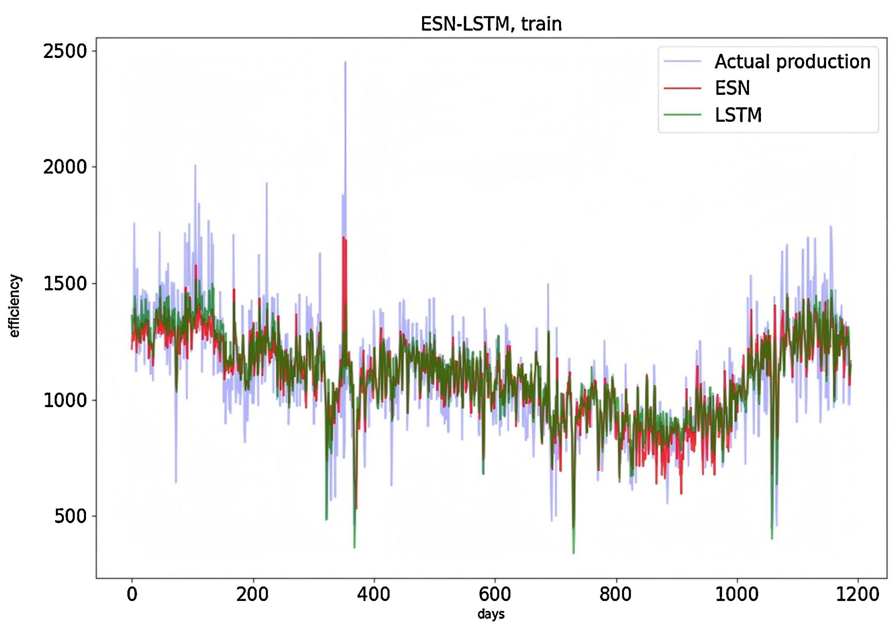

Figure 6. Prediction results of the training set.

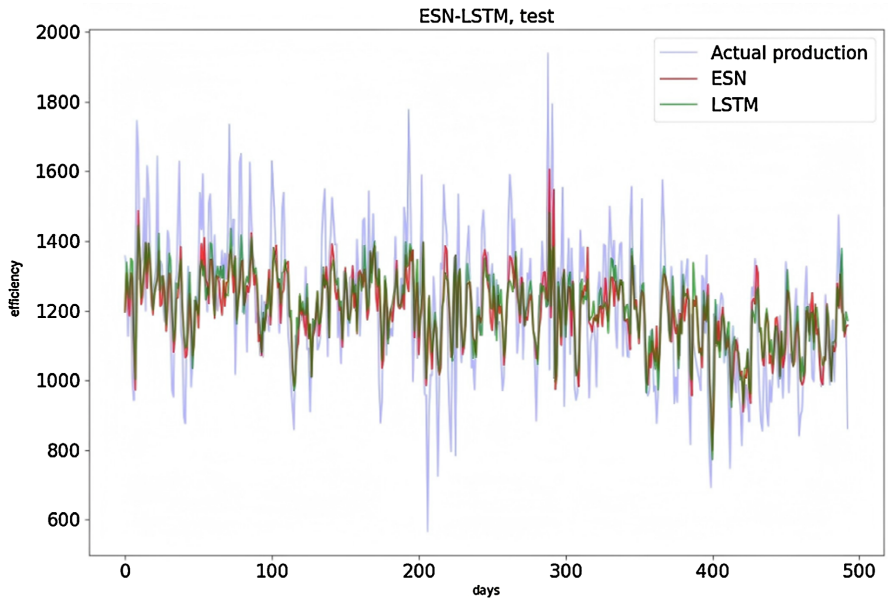

Figure 7. Prediction results of the test set.

Table 2. Comparison of the models' results.

Model	Training Time	Test MAE	Test MSE	Improvement (MAE/MSE)
RNN	4.8556 seconds	150.75	36,649.27	0%/0%
ARIMA	1.2497 seconds	171.34	45,877.36	−13.66%/−25.18%
CEEMDAN-ESN	0.3496 seconds	126.45	27,390.25	16.12%/25.26%
Bi-ALSTM	30.0662 seconds	123.47	25,475.36	18.10%/30.50%

scheduling, environmental interference), leading to ARIMA's MAE being 13.66% lower than CEEMDAN-ESN.

4. Conclusions

4.1. Summary of Model Performance

The noise separation capability of CEEMDAN addresses a key challenge in machine learning-based industrial prediction—data interference. Yuan *et al.* [7], in their study on machine learning for structural health monitoring (SHM), noted that environmental noise (e.g., vibration interference in bridge monitoring) is a major obstacle to model accuracy. This is analogous to the port operation scenario, where sudden weather changes (e.g., abrupt wind speed fluctuations) or temporary cargo handling delays (e.g., equipment downtime) introduce random noise into port efficiency signals. By decomposing the original efficiency signal into Intrinsic Mode Functions (IMFs) and a residual term, CEEMDAN effectively separates noise components from trend information, achieving a noise reduction effect comparable to the multi-source data fusion methods proposed by Yuan *et al.* This technical advantage provides high-quality, low-interference feature inputs for the subsequent Echo State Network (ESN) modeling, laying a solid foundation for balancing prediction accuracy and computational efficiency.

Based on the above technical optimization, the CEEMDAN-ESN and Bi-ALSTM models proposed in this paper exhibit significant advantages in port operation efficiency prediction: By virtue of CEEMDAN's multi-scale signal decomposition and ESN's dynamic reservoir mechanism, CEEMDAN-ESN compresses the model training time to 0.35 seconds while ensuring reliable prediction accuracy (MAE = 126.45, MSE = 27,390.25). This makes it highly suitable for scenarios requiring real-time data updates and sensitive to computational efficiency, such as real-time berth scheduling and dynamic resource adjustment in busy port periods.

In contrast, Bi-ALSTM achieves in-depth exploration of complex temporal dependencies through bidirectional temporal modeling (fusing past → future and future → past sequence information) and an attention mechanism (dynamically weighting key time-step features). Its test set MAE (123.47) and MSE (25,475.36) are 18.10% and 30.50% lower than those of the traditional Recurrent Neural Network (RNN), respectively. Moreover, it demonstrates stronger performance in long-term trend prediction (e.g., weekly port efficiency variation) and robustness to extreme values (e.g., abnormal efficiency fluctuations caused by large-scale cargo arrivals), providing high-precision decision support for strategic port management tasks such as medium- and long-term throughput planning.

4.2. Innovative Value of the Method

4.2.1. Advantages of Multi-Technology Integration

CEEMDAN effectively separates noise and trend terms in port efficiency signals, providing low-interference feature inputs for ESN and solving the limitation of traditional time-series methods in handling non-stationary data.

The bidirectional structure and attention mechanism of Bi-ALSTM break through the historical dependency limitation of unidirectional LSTM. By dynamically weighting the features of key time steps, it enhances the model's ability to represent the coupling relationship between "cargo handling and ship stay".

4.2.2. Effectiveness of Hyperparameter Optimization

A genetic algorithm is used for global search of key parameters such as the ESN reservoir size and the number of Bi-ALSTM network layers. This avoids the defect of traditional parameter tuning methods falling into local optima and realizes a systematic improvement in model performance.

4.3. Future Research Directions

While the proposed CEEMDAN-ESN and Bi-ALSTM models achieve favorable performance in port operation efficiency prediction for the Port of New York, future work will focus on addressing key gaps to enhance their practical value, with a core focus on improving cross-port generalizability and implementing systematic cross-port validation, alongside targeted complementary optimizations.

First, regarding cross-port generalizability, the current models have not been tested across diverse port contexts, and port characteristics that directly shape operational efficiency patterns and data distribution vary significantly: large automated hub ports (e.g., Port of Shanghai) differ from small manual regional ports in berthing efficiency and throughput cycles; container-dominant ports (with stable daily cycles) contrast with bulk cargo ports (prone to seasonal efficiency fluctuations); coastal ports (affected by tides and fog) and inland river ports (constrained by water levels) also introduce unique noise into efficiency signals. Such heterogeneity may lead to performance degradation when the models are directly transferred to non-target ports. To address this, future work will integrate port-specific meta-features (e.g., port scale, dominant cargo type, geographical constraints) into feature engineering, enabling the models to adaptively adjust key parameters—such as attention weights in Bi-ALSTM and reservoir settings in ESN—based on the target port's traits.

Second, to rigorously verify cross-port generalizability, a streamlined cross-port validation framework will be established. This includes selecting a set of multi-type ports (covering different scales, cargo types, and regional locations) as validation targets; standardizing operational data from these ports (unifying metrics like "daily net tonnage" calculation and sampling frequency) while preserving port-specific variations; and introducing two core evaluation metrics: Generalization Error Rate (GER), which measures the percentage increase in MAE when applying models trained on New York Port data to target ports, and Adaptation Efficiency (AE), which reflects the ratio of model performance improvement (after fine-tuning) to the volume of local data required. Additionally, drawing on the transfer learning framework proposed by Wang *et al.* for port state control, the validation process will weight data from "similar ports" (e.g., using bulk cargo port data to assist model adaptation for a bulk target port) in the source domain to reduce GER and improve AE [8].

In addition to the above, two complementary optimizations will be pursued. For spatial feature fusion, the current models focus solely on temporal dependencies of operational data (e.g., time-series changes in berthing duration) and ignore spatial correlations between port geographical layout (e.g., berth-cargo yard distance) and ship trajectories. Future work will integrate Graph Neural Networks (GNNs) to model these topological relationships, supplementing temporal features with spatial information to enhance prediction accuracy in scenarios like multi-berth collaborative scheduling. For edge computing deployment, to meet real-time port scheduling demands (e.g., dynamic crane allocation), lightweight versions of the models will be developed for edge devices (e.g., terminal control units) via methods like model pruning and parameter quantization, reducing computational latency while maintaining over 95% of the original prediction accuracy.

This research direction aims to evolve the models from a tool specific to the Port of New York into a universally applicable solution, supporting the intelligent transformation of diverse port types globally.

4.4. Summary

The intelligent prediction platform constructed in this paper significantly improves the accuracy and interpretability of port operation efficiency prediction through the technical path of "signal decomposition—feature enhancement—model optimization". It provides theoretical and methodological support for the realization of the "smart port" goal in the Outline for Building a Transport Power. Future research will focus on multi-modal data fusion and adaptive learning mechanisms to promote the evolution of port management towards full-process intelligence.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Yoon, J., Kim, D., Yun, S., Kim, H. and Kim, S. (2023) Enhancing Container Vessel Arrival Time Prediction through Past Voyage Route Modeling: A Case Study of Busan New Port. *Journal of Marine Science and Engineering*, **11**, Article 1234. https://doi.org/10.3390/jmse11061234

[2] Jaeger, H. and Haas, H. (2004) Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication. *Science*, **304**, 78-80. https://doi.org/10.1126/science.1091277

[3] Hochreiter, S. and Schmidhuber, J. (1997) Long Short-Term Memory. *Neural Computation*, **9**, 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

[4] Olah, C. (2015) Understanding LSTM Networks. https://colah.github.io/posts/2015-08-Understanding-LSTMs/

[5] Kumar, I., Tripathi, B.K. and Singh, A. (2023) Attention-Based LSTM Network-Assisted Time Series Forecasting Models for Petroleum Production. *Engineering Applications of Artificial Intelligence*, **123**, Article 106440. https://doi.org/10.1016/j.engappai.2023.106440

[6] Ning, Y., Kazemi, H. and Tahmasebi, P. (2022) A Comparative Machine Learning Study for Time Series Oil Production Forecasting: ARIMA, LSTM, and Prophet. *Computers & Geosciences*, **164**, Article 105126. https://doi.org/10.1016/j.cageo.2022.105126

[7] Yuan, F., Zargar, S.A., Chen, Q. and Wang, S. (2020) Machine Learning for Structural Health Monitoring: Challenges and Opportunities. *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems* 2020, **11379**, Article 1137903. https://doi.org/10.1117/12.2561610

[8] Wang, R., Zhang, M., Gong, F., Wang, S. and Yan, R. (2025) Improving Port State Control through a Transfer Learning-Enhanced Xgboost Model. *Reliability Engineering & System Safety*, **253**, Article 110558. https://doi.org/10.1016/j.ress.2024.110558