Research on Freight Rate Prediction of China-Europe Route Based on Bilstm Model and AIS Data

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Abstract. In the context of globalization, the shipping industry plays a crucial role in international trade, and fluctuations in freight rates have significant impacts on the global economy. This study integrates Automatic Identification System data with shipping schedule data to calculate the daily total capacity and average capacity of ships, which serve as key factors influencing freight rate predictions. By incorporating real-time AIS data, the model captures dynamic ship movements and provides more accurate capacity estimates. A Bidirectional Long Short-Term Memory model is employed and compared with Long Short-Term Memory and Recurrent Neural Network models. Additionally, hyperparameter optimization methods including Tree-structured Parzen Estimator, Bayesian Optimization, Random Search, and Grid Search are applied and compared. The results indicate that the Bilstm model with AIS data outperforms the other models in terms of Mean Absolute Error, Mean Absolute Percentage Error, and Coefficient of Determination. Among the optimization methods, the TPE method demonstrates superior performance, providing the most accurate and reliable freight rate predictions. This study highlights the importance of integrating real-time AIS data and advanced optimization techniques in improving the accuracy of freight rate prediction models

Keywords: component; Shipping; Freight Rate Prediction; AIS; Bilstm.

1 Introduction

In today's globalized world, the shipping industry serves as a critical component of international trade, with fluctuations in freight rates having significant implications for the global economy. Shipping freight rates not only impact the revenues of shipping companies and cargo owners but also play a crucial role in the stability of the global supply chain. Accurate prediction of freight rates can aid businesses in making more effective operations and decisions, thereby enhancing market competitiveness.

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1.1 Current Time Series Forecasting Methods

The volatility of shipping freight rates is influenced by numerous factors, including market supply and demand, fuel prices, weather conditions, and political factors. Therefore, accurate prediction of freight rates is of great importance for shipping companies in formulating reasonable pricing strategies, optimizing capacity allocation, and reducing operational risks. For cargo owners, understanding future freight rate trends can help in better planning logistics costs, selecting the optimal transportation scheme, thereby saving costs and improving operational efficiency. Additionally, freight rate prediction assists cargo owners in risk management, avoiding uncertainties caused by rate fluctuations. Accurate freight rate predictions can also enable governments to take timely measures during market anomalies to prevent market imbalance and protect stakeholders' interests. Thus, predicting shipping freight rates is not only a core requirement for shipping companies and cargo owners but also an essential aspect of ensuring stable global trade and economic development.

In recent years, machine learning and deep learning techniques have been widely applied in freight rate forecasting. Research by Hirata and Matsuda [1] demonstrated that the LSTM model outperforms the SARIMA model on most datasets. Saeed et al. [2] significantly improved the accuracy of predictions by incorporating perturbation events into the Prophet forecasting model, especially when considering market volatility factors. Munim and Schramm [3] compared the ARIMA and ARIMARCH models, finding that the latter performs better in short-term forecasting, particularly in handling freight rate fluctuations.

Benth and Koekebakker [4] proposed a continuous-time process model to simulate the dynamics of Supramax freight rates, demonstrating its advantages in capturing market volatility. Yang and Mehmed [5] showcased the application of two dynamic artificial neural network models, NARNET and NARXNET, in freight rate forecasting, proving their effectiveness in multi-step forecasting.

Podlodowski and Kozłowski [6] enhanced the prediction accuracy of transshipment contract costs by combining XGBoost and deep neural networks. Syriopoulos et al. [7] applied Support Vector Machines (SVM) for vessel price forecasting, finding that its predictive performance surpasses that of traditional time series models.

1.2 AIS Data and Freight Rate Data

The Automatic Identification System (AIS) data plays a pivotal role in the shipping industry, primarily by providing real-time tracking of vessel positions, speeds, and course information. AIS data aids market participants in better understanding market dynamics and making informed decisions. By collecting and analyzing AIS data, shipping companies can optimize vessel routes, enhance operational efficiency, and promptly respond to maritime emergencies. Additionally, port management authorities can utilize this data for berth allocation, port scheduling, and congestion management, thereby improving port operation efficiency. Governments and regulatory agencies can also monitor maritime traffic, enforce safety regulations, and implement environmental protection measures using AIS data. AIS data significantly contributes to enhancing the overall efficiency of the shipping industry, ensuring navigational safety, and promoting sustainable development.

By incorporating AIS data, the daily estimation of shipping capacity can be more accurately determined, thereby improving the accuracy of freight rate forecasts. Koyuncu and Tavacıoğlu [8] used AIS data in conjunction with time series models to enhance the prediction accuracy of the Shanghai Containerized Freight Index (SCFI). Chen et al. [9] improved the prediction accuracy of dry bulk market freight rates by combining AIS data with market sentiment indicators. Lim and Kim [10] successfully forecasted freight rate fluctuations in the dry bulk and tanker markets by combining AIS data with wavelet decomposition and empirical mode decomposition techniques.

Additionally, the study by Dong Liangcai et al. [11] showed that a fuzzy neural network model incorporating AIS data could more accurately predict the Baltic Dry Index (BDI), enhancing the handling of complex nonlinear data. Li Wanyong et al. [12] significantly improved the prediction accuracy of the China Containerized Freight Index (CCFI) by integrating AIS data with an ANN-ARIMA combined model. Lan Xiangang's [13] research demonstrated the efficiency of the SVR-Adam-LSTM model, combined with AIS data, in predicting the Baltic Dry Index.

In summary, this study distinctively incorporates daily total capacity and average capacity of ships into freight rate prediction models using AIS data. This approach significantly enhances the accuracy of the BiLSTM model, providing stakeholders with more reliable decision support. By addressing the inherent volatility and uncertainties of the shipping market, this method demonstrates substantial improvements in the precision and reliability of freight rate forecasts.

2 Methodology

2.1 Calculation of Shipping Route Capacity

Using a combination of shipping schedule data and AIS data, the capacity supply on the Tianjin-Europe route was calculated by analyzing the number and capacity of ships on this route. AIS data plays a crucial role in the shipping industry, primarily used to track the real-time location, speed, and course of ships. To calculate the capacity supply on the Tianjin-Europe route, the shipping schedule data was combined with AIS data. The specific formula is as follows:

$$I(t) = \begin{cases} 1 & \text{if } P_t \in R \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$C_d = \sum_i T \times I_i(d) \tag{2}$$

$$N_d = \sum_i I_i(d) \tag{3}$$

$$C_{\text{avg},d} = \frac{C_d}{N_d} \tag{4}$$

In these formulas, p_t represents the real-time position data of the ship at time t. The geographic range of the Tianjin-Europe route is denoted by R. The binary function $I(t)$ indicates whether a ship is on the route at time t. The variable d refers to a specific day, and C_d is the daily total capacity on that day. The number of ships on the route on day d is represented by N_d. The index of the ship is i, and T_i is the TEU of the i-th ship. The binary function $I_i(d)$ indicates whether the i-th ship is on the route on day d. Finally, $C_{\text{avg},d}$ is the average daily capacity on day d.

2.2 Current Time Series Forecasting Methods

In data preprocessing, several interpolation methods were used to handle missing values and compare their impact on model performance. Specifically, linear interpolation, quadratic interpolation, cubic interpolation, and Pchip interpolation methods were utilized. The formulas for these interpolation methods are as follows:

Linear Interpolation formula is as follows:

$$y = y_1 + \frac{(x - x_1)}{x_2 - x_1}(y_2 - y_1) \tag{5}$$

Quadratic Interpolation formula is as follows:

$$\begin{aligned} P(x) &= a_0 + a_1(x - x_0) \\ &+ a_2(x - x_0)(x - x_1) \end{aligned} \tag{6}$$

Cubic Interpolation formula is as follows:

$$\begin{aligned} P(x) &= a_0 + a_1(x - x_0) + a_2(x - x_0)^2 \\ &+ a_3(x - x_0)(x - x_1)(x - x_2) \end{aligned} \tag{7}$$

Pchip Interpolation formula is as follows:

$$h_{00}(t) = (1 + 2t)(1 - t)^2 \tag{8}$$

$$h_{10}(t) = t(1 - t)^2 \tag{9}$$

$$h_{01}(t) = t^2(3 - 2t) \tag{10}$$

$$h_{11}(t) = t^2(t-1) \tag{11}$$

$$t = \frac{x - x_i}{x_{i+1} - x_i} \tag{12}$$

Using these basis functions, the Hermite interpolating polynomial can be expressed as:

$$\begin{aligned} p_i(x) &= h_{00}(t)y_i + h_{10}(t)(x_{i+1} - x_i)m_i \\ &+ h_{01}(t)y_{i+1} + h_{11}(t)(x_{i+1} - x_i)m_{i+1} \end{aligned} \tag{13}$$

In these formulas, y represents the interpolated value, which is the estimated value at a given interpolation point x. The coordinates x_0, x_1, x_2 are the known points on the x-axis, while y_0, y_1, y_2 are the corresponding known values on the y-axis. The coefficients a_0, a_1, a_2 and a_3 are the polynomial coefficients used in quadratic and cubic interpolation. The variable t is the normalized interpolation point. The Hermite basis functions $h_{00}(t)$, $h_{10}(t)$, $h_{01}(t)$ and $h_{11}(t)$ are used to construct the Hermite interpolating polynomial. In this polynomial, y_i and y_{i+1} are the function values at the nodes, m_i and m_{i+1} are the derivative values at the nodes.

2.3 Bilstm Model Structure

The Long Short-Term Memory (LSTM) model is an improved Recurrent Neural Network (RNN) particularly suited for handling and predicting time series data. Its key innovation lies in introducing memory cells that control the flow and retention of information through three gate mechanisms: forget gate, input gate, and output gate, as illustrated in Fig. 1.

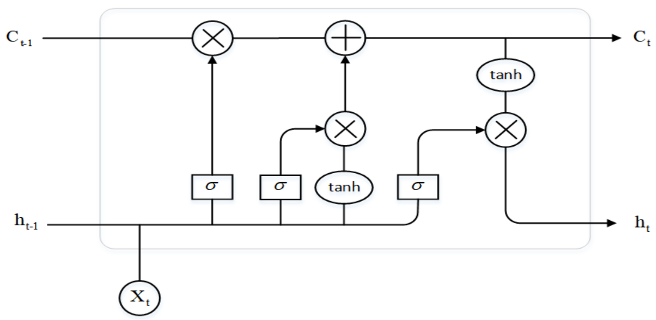

Fig. 1. LSTM Model.

The formula is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f) \tag{14}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \tag{15}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{16}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \tag{17}$$

$$h_t = o_t \odot \tanh(C_t) \tag{18}$$

In these formulas, x_t represents the input vector at the current time step, h_{t-1} represents the hidden state at the previous time step, C_{t-1} represents the cell state at the previous time step, C_t represents the cell state at the current time step, and h_t represents the hidden state at the current time step. σ is the sigmoid activation function, W_f, W_i, and W_o are the weight matrices for the forget, input, and output gates, respectively, b_f, b_i, and b_o are the bias vectors for the corresponding gates, $\odot$ denotes element-wise multiplication, and $\tilde{C}_t$ is the candidate cell state obtained through certain transformations.

The Bidirectional Long Short-Term Memory (Bilstm) model captures contextual information of time series data more effectively by combining forward and backward LSTM layers (as shown in Fig. 2). This structure allows the network to consider both past and future information, thereby improving prediction accuracy.

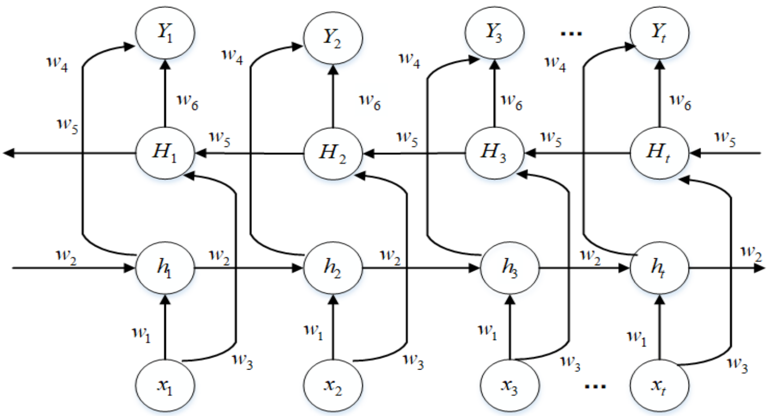

Fig. 2. Bilstm Network Architecture Diagram.

In the Bilstm model, the input vector X_t represents the input data at the current time step, h_t denotes the forward hidden state, and H_t denotes the backward hidden state. The output vector Y_t represents the output at the current time step. The weight parameters w_t (t=1,2,3...6) are used to connect the relationships between the inputs, hidden states, and outputs. Through these weights, the Bilstm model can effectively capture the contextual information of time series data, thereby improving prediction accuracy.

2.4 TPE Optimization Algorithm

The Tree-structured Parzen Estimator (TPE) algorithm is a Bayesian optimization method used for hyperparameter tuning. TPE constructs probabilistic models and iteratively selects new hyperparameter combinations based on Bayesian updating rules, effectively searching for optimal solutions in high-dimensional spaces.

The formula is as follows:

$$l(x) = p(x \mid y \le \gamma) \tag{19}$$

$$g(x) = p(x \mid y > \gamma) \tag{20}$$

$$EI(x) = \int_{-\infty}^{\gamma} (\gamma - y) l(y \mid x) dy \tag{21}$$

In these formulas, y represents the objective function value, and x represents the hyperparameter combination. The symbol γ is the threshold value that is dynamically updated during the optimization process. The functions $l(x)$ and $g(x)$ represent the probability density distributions of the hyperparameter x when the objective function value y is less than or equal to γ and greater than γ, respectively. The term $EI(x)$ represents the Expected Improvement, which is used as the sampling criterion to select new sampling points in the optimization process.

Combining Bilstm and TPE optimization can effectively enhance the accuracy of freight rate forecasts.

2.5 Bilstm-TPE Model Structure

The AIS-Bilstm-TPE model combines the bidirectional information capturing capability of Bilstm with the efficient hyperparameter optimization method of TPE, continuously optimizing model parameters to improve the accuracy of freight rate predictions. This model integrates shipping freight rate data, AIS data, and shipping schedule data, aligning them in time to form daily ship data. The daily ship data undergoes interpolation to handle missing values, and the resulting data is split into freight rate, total TEU, and average TEU. These features are then fed into a Bidirectional LSTM network, optimized by the TPE optimizer, to produce the final forecast results. (as shown in Fig. 3).

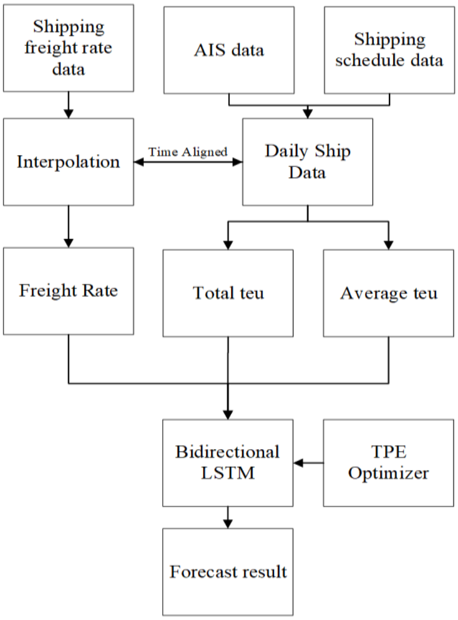

Fig. 3. AIS-Bilstm-TPE Model.

With this architecture, the model can effectively capture market supply-demand dynamics and freight rate trends, providing more accurate prediction results.

3 Experiment Design

3.1 Experimental Data

The experimental data used in this study comes from the shipping schedules provided by China Shipping Gazette and AIS data provided by the Shipping & Port Big Data Laboratory (SPBD-Lab). The selected features include price, total TEU, and average TEU. To verify the effectiveness of the AIS-Bilstm-TPE model, this study uses the freight rates for the Tianjin-Europe route for the entire year of 2022 as the dataset, and the capacity data of the Tianjin-Europe route as an influencing factor to optimize the shipping freight rate prediction.

3.2 Evaluation Metrics

This study uses the following metrics to evaluate the model's performance:

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{22}$$

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{23}$$

Mean Absolute Percentage Error:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \tag{24}$$

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \tag{25}$$

In these formulas, n represents the number of samples, y_i is the actual value of the i-th sample, $\hat{y}_i$ is the predicted value of the i-th sample, and $\overline{y}$ is the mean value of the samples.

3.3 Data Preprocessing

Data loading and preprocessing include using MinMaxScaler to normalize the data, scaling it between 0 and 1. The normalization formula is as follows:

$$x_{new} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{26}$$

Where X_{new} is the normalized data, x is the original data value, $X_{\max}$ is the maximum value in the dataset, and $X_{\min}$ is the minimum value in the dataset.

This study uses the first 70% of the data as the training set and the remaining 30% as the test set. The TPE algorithm is used for hyperparameter optimization, including optimizing the hidden layer size, number of layers, learning rate and dropout rate. The Mean Squared Error loss function is used as the optimization objective function. The models were trained and the loss on the validation set was calculated. Subsequently, the models were retrained using the best parameters, with the Early Stopping strategy adopted to prevent overfitting.

3.4 Interpolation Methods Analysis

By comparing the results of different interpolation methods (Table 1), we found that the Pchip interpolation method performed best in terms of MAE and RMSE (Formula22,23).

Table 1. Comparison of interpolation methods.

	MAE	RMSE
Linear Interpolation	50.54	100.94
Quadratic Interpolation	53.08	104.58
Cubic Interpolation	53.96	105.03
Pchip Interpolation	49.25	100.49

3.5 Predictive Model Comparative Analysis

During the model training process, this study conducted a comparative analysis of Bilstm, LSTM, and RNN models. To ensure a fair comparison, the TPE algorithm was employed for hyperparameter optimization for each model, with the number of optimization iterations set to 30.

The fixed values include setting the weight decay to 0.01, the batch size to 32, the total number of training epochs to 200, and the patience for early stopping to 50. The hyperparameters optimized using the TPE algorithm include hidden size, with a range set between 10 and 100; num layers, set within the range of 1 to 4 layers; learning rate, specified as a float between 0.001 and 0.01, distributed on a logarithmic scale; and dropout probability, set between 0.2 and 0.5. The specific values for these hyperparameters were determined using the Optuna framework.

For the performance evaluation of each model, metrics such as Mean Squared Error, Mean Absolute Error, and Coefficient of Determination were used for comparison (Formula22,24,25). These metrics provide a comprehensive assessment of each model's performance in time series prediction, particularly in handling complex dependencies and long-term data.

The comparison chart of the prediction results and actual values shows that the prediction curve of the Bilstm model with AIS data is the closest to the actual values, indicating the highest prediction accuracy. In contrast, the prediction curves of Bilstm, LSTM, and RNN show larger deviations from the actual values. (as shown in Figure 4).

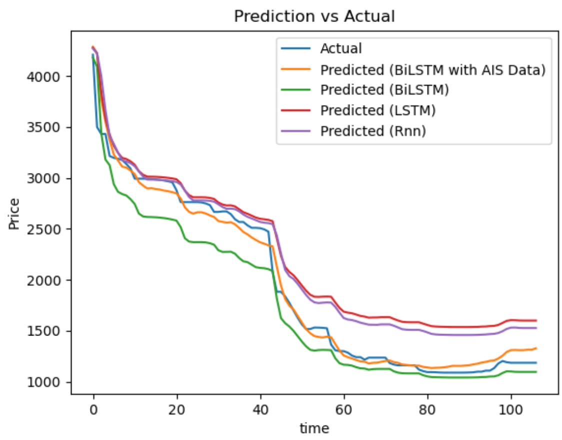

Fig. 4. Comparison of prediction model results.

Especially in the long-term interval, the Bilstm model with AIS data can better follow the trend of actual values, while the other models exhibit larger deviations. This further validates the advantage of the Bilstm model with AIS data in handling long-term data.

Table 2. Comparison of Predictive Model.

	MAE	**MAPE**	**R2**
Bilstm with AIS Data	79.41	0.044	0.9816
Bilstm	195.80	0.094	0.9179
LSTM	288.57	0.21	0.8393
Rnn	244.53	0.18	0.8796

The results show that the Bilstm model combined with AIS data outperforms all other models across all evaluation metrics. (as shown in Table 2).Its MAE is 79.4129, MAPE is 0.0438, and R^2 is 0.9816. Although LSTM and RNN models are able to capture patterns in time series to a certain extent, their predictive performance is rela-tively poor. This indicates that the Bilstm model with AIS data can better capture bidirectional dependencies in time series data, significantly improving prediction accuracy.

In summary, the Bilstm model with AIS data demonstrates outstanding performance in time series prediction, significantly improving prediction accuracy and stability, making it an effective prediction method.

3.6 Optimization Model Comparative Analysis

In the Bilstm model with AIS data, this study compared the impact of different optimization methods on model performance. The specific optimization methods used include TPE, Bayesian Optimization, Random Search, and Grid Search. Each method was optimized 30 times, with the loss values recorded during the optimization process. (as shown in Fig. 5)

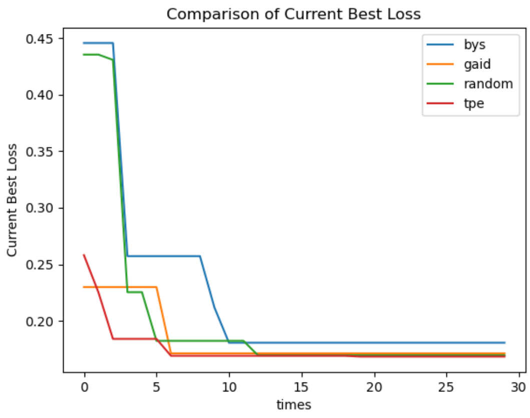

Fig. 5. Optimization process.

The comparison of loss values during the optimization process shows significant differences in the performance of different optimization methods over 30 iterations(Fig. 5). The TPE method quickly reduces the loss value in the early stages and stabilizes after a few iterations, demonstrating its efficiency and stability in finding the optimal parameter combination. The Random Search method also shows a rapid decrease in loss value initially, but its final loss value is slightly higher than that of TPE. (as shown in Figure 6) The Bayesian Optimization method and Grid Search method exhibit slower loss value reduction and higher final loss values, indicating that their optimization effectiveness is inferior to that of TPE and Random Search.

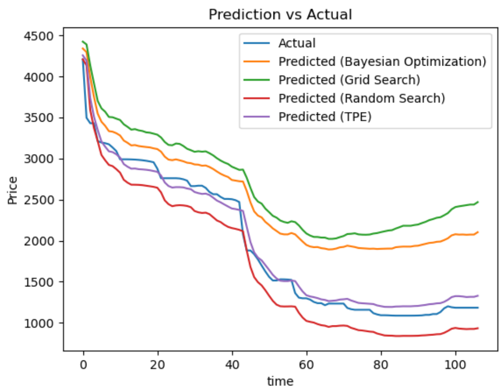

Fig. 6. Comparison of optimization model results.

The comparison chart of the prediction results and actual values shows that the prediction curve of the Bilstm model optimized with TPE is the closest to the actual values, indicating the highest prediction accuracy. In contrast, the prediction curves of Bayesian Optimization, Random Search, and Grid Search show larger deviations from the actual values.

Table 3. Comparison of Optimization Model.

	MAE	MAPE	R2
Bayesian Optimization	549.69	0.40	0.4695
Grid Search	741.81	0.53	0.08708
Random Search	258.16	0.16	0.8967
TPE	95.92	0.059	0.9785

The table data indicates that the Bilstm model optimized with TPE outperforms all other optimization methods across all evaluation metrics. (as shown in Table 3). Specifically, the TPE-optimized Bilstm model has an MAE of 95.92, MAPE of 0.059, and R^2 of 0.9785. This demonstrates that the TPE method has a significant advantage in hyperparameter optimization, significantly improving the model's prediction accuracy and stability. Although Bayesian Optimization and Random Search can improve model performance to some extent, their optimization effects are still inferior to the TPE method.

4 Conclusion

This study developed a freight rate prediction model for the China-Europe route using the BiLSTM model combined with AIS data and compared its performance with other models, including LSTM and RNN. The integration of AIS data allowed for more accurate estimation of ship capacities, which significantly improved the predictive performance of the models. The experimental results indicate that the BiLSTM model with AIS data significantly outperforms the LSTM and RNN models in terms of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

4.1 The Role of AIS Data

The integration of AIS data played a crucial role in enhancing the predictive accuracy of the BiLSTM model. By combining AIS data with shipping schedule data, we were able to calculate the daily total capacity and average capacity of ships on the China-Europe route. These capacity metrics provided valuable insights into the supply side of the freight market, which significantly impacted the accuracy of freight rate predictions. The use of real-time AIS data enabled the model to capture the dynamic nature of shipping operations, leading to more precise and reliable forecasts.

4.2 Model Selection and Hyperparameter Optimization

The comparative analysis of different models demonstrated that the BiLSTM model, especially when combined with AIS data, outperformed LSTM and RNN models. The BiLSTM model's ability to capture bidirectional dependencies in time series data led to significantly improved prediction accuracy. This highlights the importance of model selection in achieving high-performance freight rate predictions.

In terms of hyperparameter optimization, the TPE method proved to be highly effective. The BiLSTM model optimized with TPE showed the best performance, with the lowest MAE, MAPE, and highest R^2 values among all optimization methods tested. The TPE method quickly reduced the loss value in the early stages and stabilized, indicating its efficiency and stability in finding the optimal parameter combination. In contrast, Bayesian Optimization, Random Search, and Grid Search were less effective.

4.3 Implications for Future Research and Practice

The findings of this study suggest that the BiLSTM model combined with AIS data and optimized using the TPE method provides a robust and accurate approach for predicting freight rates on the China-Europe route. This model can help shipping companies and cargo owners make more informed decisions, optimize operations, and manage risks more effectively. The successful integration of AIS data highlights the importance of real-time data in improving the accuracy and reliability of predictive models. Future research could further explore the application of other real-time data sources and advanced optimization techniques to continue improving the performance of freight rate prediction models.

In summary, the integration of AIS data, the application of the BiLSTM model, and the use of the TPE optimization method collectively enhance the prediction accuracy and reliability of freight rate forecasts. This contributes to better decision-making and operational efficiency in the shipping industry, ultimately supporting more stable and sustainable global trade.

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