• Article •

Research on BDI Index Prediction Based on LSTM Neural Network

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Abstract: This study utilizes the Long Short-Term Memory (LSTM) neural network model to predict the Baltic Dry Index (BDI), a crucial indicator of the global economy and international trade. By analyzing historical data and related economic indicators of the BDI, a dataset incorporating multiple time series characteristics was constructed. The study finds that a univariate LSTM model demonstrates higher accuracy and stability in predicting the BDI index due to its ability to capture nonlinear dynamic features. This model can provide market trend forecasts for investors, assist in formulating investment strategies, and support economic policy decisions for government policymakers in adapting to changes in international trade and shipping markets. The results indicate that the LSTM model has practical value in financial market forecasting and offers a new direction for the application of deep learning technology in this field.

Keywords: Shipping Market; LSTM Model; BDI Index; Index Forecasting

1. Introduction

Since the time of Adam Smith, trade has been recognized as a catalyst for economic development. Through trade between nations, the uneven distribution of resources across different countries has been addressed. The shipping market, as a vital facilitator of international trade, has successfully overcome the barrier of distance in international trade, making the connections between international trade more tightly knit. Ocean transportation, as an important mode of long-distance transport, boasts advantages such as large cargo capacity, a wide variety of goods that can be transported, and low unit transportation costs.

The Baltic Exchange is the world's first shipping market futures exchange. The Baltic Dry Bulk Freight Index (BDI) is a comprehensive index composed of freight rates from several traditional dry bulk shipping routes, weighted according to their importance and proportion in the shipping market. It is one of the most important indices in the global shipping market and is considered a barometer and weathervane for the entire international dry bulk shipping market. In recent years, due to unstable international situations and the impact of the pandemic, market supply and demand have changed rapidly, leading to significant fluctuations in the BDI index, which affects the operation of the international trade market. Moreover, compared to other futures indices, the BDI index is not easily manipulated by governments or speculative institutions and is entirely determined by the spontaneous equilibrium of market supply and demand. Therefore, accurately predicting the trend of the BDI index is beneficial to the development of the entire shipping market.

Current research on BDI index forecasting focus on traditional time series analysis methods, machine learning methods, and deep learning methods. Given the high volatility and non-stationary nature of shipping market data, accurate prediction of the BDI index has always been a hot topic in current shipping research. Utilizing LSTM models to analyze and forecast the time series of the BDI index, neural network models can effectively handle long-term dependencies in time series data, giving LSTM models an advantage in predicting long-term sequence data of the BDI index. In terms of the complexity and non-stationarity of data, LSTM models can also learn and capture features within the data, thereby enhancing the accuracy and reliability of the forecast results.

2. Literature Review

The Baltic Dry Index (BDI), as a barometer of the international dry bulk shipping market, has always been a focus of attention. In recent years, with the fluctuations in the global economy and the recovery of the shipping industry, the changes in the BDI index and the analysis of its influencing factors have become hot topics in academic research. This paper provides a review of the current state of research on the factors influencing the BDI index from multiple perspectives.

2.1 Literature Review on the Factors Influencing the BDI Index

Firstly, from the perspective of the global economy and trade, many scholars have explored the association between the BDI index and economic conditions and trade activities. Gao, Ruzhao et al. analyzed the linear and nonlinear Granger causal relationships between global economic policy uncertainty and the BDI index, concluding that the causal relationship between them changes over time. Tiwari, A.K. (2024) studied the impact of the shipping market on the commodity market, concluding a two-way causal relationship between shipping market freight prices and the commodity market. Ma Shaohui et al. (2017), through cointegration tests and causal analysis, revealed a one-way Granger causal relationship between the BDI index and the order volume of dry bulk ships, indicating that global trade demand has a significant impact on the BDI index. At the same time, Lan Xian Gang (2023), when analyzing the fluctuations of the BDI index, also emphasized the impact of international oil price trends on the BDI index, reflecting the important role of global economic factors in the shipping market.

Secondly, the ship market factors are also one of the key factors affecting the BDI index. Zhang Yongfeng et al. (2016) used the GARCH model to analyze the correlation between commodity trade and the capital market, revealing the close connection between the ship market and the capital market.

Wu Huahua et al. (2019) used the VMD-FFT-LSTM combined forecasting model to improve the prediction accuracy of the BDI index, further proving the importance of ship market factors in predicting the BDI index.

In addition, some scholars have explored the influencing factors of the BDI index from other perspectives. For example, Gu, YM. (2019) studied the interaction between the BDI index and iron ore spot prices under the new pricing mechanism, indirectly illustrating the impact of iron ore prices on the BDI index; besides the controlled variables, a significant spillover interaction between BDI and the iron ore market was found. Liu Bin et al. (2010), by comparing the BDI index with the Shanghai Composite Index, found a positive correlation between the two, revealing the impact of the capital market on the BDI index. Wang Xian (2023) used EMD algorithm and machine learning models to perform frequency decomposition and predictive analysis on the influencing factors of the BDI index, providing new ideas and methods for the prediction of the BDI index.

This review highlights the multifaceted nature of the BDI index, with its fluctuations being influenced by a complex interplay of global economic conditions, trade activities, ship market dynamics, and other factors. The ongoing research in this area aims to provide a more comprehensive understanding of these influences and to develop more accurate forecasting models for the BDI index.

2.2 Research Status of LSTM Neural Network Models

With the rapid development of big data and artificial intelligence technologies, Long Short-Term Memory (LSTM) models, as an important branch of deep learning, have been widely applied in various fields such as time series prediction, natural language processing, and speech recognition. Particularly in the area of financial time series forecasting, LSTM models have gradually become a research hotspot due to their strong memory capabilities and nonlinear fitting abilities. Scholars both domestically and internationally have conducted extensive research on this topic.

For instance, Bae, S.-H. (2021) utilized deep learning models to predict the trends of the Baltic Dry Index (BDI), comparing the forecasting effects of algorithms such as Recurrent Neural Networks (RNN) and determining the optimal parameters. Yang Chen et al. (2023) employed a combination of Empirical Mode Decomposition (EMD) and LSTM models for predicting international gold futures prices, conducting an empirical analysis on gold futures price data from 2011 to 2021. The results indicated that the LSTM neural network model had better predictive accuracy, providing a more effective method for investment decisions in the gold futures market.

In the field of stock index prediction, Yang Qing et al. (2019) compared the performance of LSTM models with Support Vector Regression (SVR), Multilayer Perceptron (MLP), and Autoregressive Integrated Moving Average (ARIMA) models in forecasting 30 global stock indices, finding that LSTM neural network models demonstrated excellent predictive accuracy for different time horizons of stock indices. Peng Yan et al. (2019), in response to the volatility characteristics of the stock market, built network models with different numbers of LSTM layers, effectively improving the accuracy of stock price predictions and providing valuable references for stock trend forecasting.

Additionally, Ouyang Hongbing et al. (2020) combined wavelet analysis with LSTM models to model and predict the closing prices of the Dow Jones Industrial Average; through comparisons with various models, it was found that LSTM neural network models had higher predictive accuracy, providing a scientific basis for investment decisions in the financial market. In terms of stock index prediction, Li Jia et al. (2019) used LSTM neural networks and other deep learning technologies for an in-depth analysis of China's CSI 300 Index and Shanghai Composite Index, finding that LSTM models showed higher precision in predicting stock indices, offering valuable reference information for investors. Zhang Wei et al. (2022) conducted an LSTM network prediction study on the stock prices of China's petroleum industry, discovering through comparisons with traditional time series analysis methods that LSTM had better predictive capabilities and stability when dealing with nonlinear and highly volatile financial time series data, providing strong support for investment decisions in the petroleum market. Yao Honggang et al. (2021) compared the standard LSTM model with prediction methods combined with EMD, using the Shanghai Composite Index data for empirical analysis. The results showed that the proposed EMD-LSTM model had better predictive effects, offering investors more accurate market trend predictions.

In summary, existing research primarily utilizes neural network models for predictive analysis of time series indices; due to the influence of multiple international factors on the BDI index, there is a scarcity of predictive research on the BDI index. Some literature only examines the macroeconomic factors affecting the BDI index without further subdividing these factors from multiple perspectives. Additionally, there is a lack of research that continues to decompose the prediction of the BDI index using existing machine learning models based on the analysis of influencing factors.

Accordingly, the marginal contributions of this paper are mainly reflected in the following two aspects: First, in terms of analyzing influencing factors, the paper subdivides the main influencing factors for different industries and identifies the primary micro-level factors of each macroeconomic factor through various causal analysis methods. This provides a new approach for in-depth research on the influencing factors of the BDI index. Second, in terms of predicting the BDI index, the paper innovates and optimizes the prediction model by constructing a four-factor LSTM model based on the analysis of specific influencing factors, and compares the results with those of single time series models, providing empirical support for the innovation of BDI index prediction models.

3. Analysis of Factors Influencing the BDI Index

The Baltic Dry Index (BDI) is published by the world-renowned Baltic Exchange, which succeeded the Baltic Freight Index (BFI) launched in 1985. The BFI was initially designed to reflect changes in international dry bulk shipping rates, with a base point of 1,000, and was composed of freight and charter rates from 13 internationally significant shipping routes. The cargoes covered by these routes primarily consisted of bulk commodities such as iron ore, coal, crude oil, and grain.

As international trade continues to evolve, the number of shipping routes has increased, and freight rates have fluctuated, leading to constant adjustments in the weighted proportions of freight rates for different routes. In 1999, the Baltic Exchange restructured the BFI into three components based on different ship types: the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI), and the Baltic Handsize Index (BHSI), expanding the number of routes to 24.

The Baltic Handsize Index (BHSI) is categorized based on the deadweight of the vessels, generally referring to dry bulk carriers with a capacity between 50,000 and 60,000 tons. With the development of international trade, distinct differentiations emerged in different handysize vessel markets. In 2005, the Baltic Exchange introduced the Baltic Supramax Index (BSI) and adjusted the BDI to consist of four parts: the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI), the Baltic Handsize Index (BHI), and the Baltic Supramax Index (BSI), with each index contributing 25% to the BDI.

After 2009, to more accurately reflect changes in the international shipping market, the average rental was adopted as the calculation standard for the BDI. Concurrently, due to the continuous increase in international trade routes, the calculation of the BDI underwent several adjustments. Since the 2017 revision, the BDI has been composed of three weighted parts: the Baltic Capesize Index (BCI) accounting for 40%, the Baltic Panamax Index (BPI) accounting for 30%, and the Baltic Supramax Index (BSI) accounting for 30%, forming an average rental index.

The BDI index is influenced by a multitude of factors, including but not limited to:

1. Global Economic Conditions: The state of the global economy significantly impacts the demand for dry bulk commodities, thereby affecting the BDI.

2. Trade Patterns: Changes in international trade patterns, such as the volume of commodities being shipped, can influence the demand for dry bulk shipping services.

3. Shipping Market Dynamics: The supply and demand dynamics within the shipping industry, including the number of vessels, their sizes, and the availability of shipping capacity, play a crucial role in determining the BDI.

4. Commodity Prices: Fluctuations in the prices of commodities like iron ore, coal, and grains can impact the volume of trade and, consequently, the BDI.

5. Geopolitical Factors: Political stability and conflicts can disrupt trade routes and affect the BDI.

6. Seasonal Variations: Certain commodities have seasonal trade patterns that can influence the BDI.

7. Technological Advancements: Improvements in ship design and fuel efficiency can impact the cost of shipping and the BDI.

8. Environmental Regulations: Changes in environmental policies and regulations can affect the operation of ships and the BDI.

Understanding these factors is crucial for stakeholders in the shipping industry, as it allows them to make informed decisions regarding fleet management, route planning, and market strategies. The BDI index serves as a key indicator for these analyses, reflecting the broader health of the global dry bulk shipping industry.

Figure3-1 BDI Index Trend

3.1 Metal Market Price Factors

The transportation of metal bulk cargo is primarily dominated by shipping. Due to the rapid development of the metal materials industry and the continuous growth of international trade in recent years, the volume of metal bulk cargo shipped has been increasing. Among them, iron ore is the metal raw material with the largest proportion of seaborne trade, accounting for about 40%. Bauxite, as the main source of aluminum, is widely traded globally. The demand for bauxite remains stable due to the application of aluminum in industries such as automobiles, construction, and packaging, thus promoting its position in the dry bulk shipping market. Copper, being an important raw material for the electrical and electronics industries, has a consistently high demand for copper ore. Long-distance transportation from large copper mines in countries like Chile and Peru to major consumer countries has increased the demand for dry bulk shipping. These metal bulk cargoes occupy a significant share in the dry bulk shipping market due to their key role in global industrial production. Their trade flows and price fluctuations have a significant impact on the supply and demand conditions of the shipping market and freight indices such as the Baltic Dry Index (BDI).

This paper mainly selects the copper futures price index, 62% iron ore price index, and bauxite futures price index data from January 1, 2013, to March 2024, as the objects of analysis for metal bulk cargo market price factors. Since the New York Mercantile Exchange (COMEX) is the world's main center for metal futures trading, the data for copper futures and bauxite futures come from COMEX; China, being the main trading country for iron ore, provides the 62% iron ore price index from Chinese futures exchanges. Data queries are all from Wind.

Since the premise of the Granger causality test is that the data is a stationary time series, we first conduct a unit root test on the multivariate time series data. As the unit root test did not pass, we difference the data and then conduct the unit root test again. The first-order differenced multivariate time series is a stationary time series. Therefore, we perform a cointegration test on this multivariate time series, and the cointegration test is significantly established at the 1% level. Table 1 shows the results of the Granger test. Through the Granger test results, we can find that there is a significant causal relationship between the BDI index and the futures prices of Al and Fe.

Table 1 Granger Causality Wald Tests

Equation	Excluded	Chi2	df	Prob>chi2
BDI	Cu	5.3389	2	0.069
BDI	Al	9.9409	2	0.007
BDI	Fe	16.276	2	0.000
BDI	ALL	32.988	6	0.000

In the Granger causality test table, the Chi2 represents the chi-squared statistic with 2 degrees of freedom, and Prob>chi2 is the p-value used for judgment in this study. When the p-value is less than 0.05, we can reject the null hypothesis, implying that the causal relationship is significant. Since this study analyzes the influencing factors of the BDI index, the experimental results only display the one-way causal relationships between the futures prices of various financial market commodities and the BDI index. At a statistically significant level of 0.05, the futures price trends of Al (aluminum) and Fe (iron) have a significant causal relationship with the BDI index.

3.2 Agricultural Product Market Price Factors

Agricultural products are indispensable raw materials in life and industrial production and constitute a highly significant component of international trade. Due to the supply and demand of agricultural products and their important position in the dry bulk shipping market, many countries around the world rely on importing these basic commodities to meet domestic needs. The transportation of agricultural products often involves the transnational shipment of large quantities of goods, especially from countries with high production but low consumption (such as Brazil, the United States, Canada, Russia, Australia, etc.) to countries with high demand (such as China, Egypt, Iran, European Union countries, etc.). In these dry bulk shipments of agricultural products, shipping is the primary mode of transportation, hence its impact on the international shipping market is self-evident. Countries with high demand for agricultural products are mainly developing nations, which have large populations but relatively lower levels of technology compared to developed countries, resulting in insufficient food production.

In global agricultural trade, exporting countries are primarily developed nations, thus these countries have a more significant advantage in market pricing of agricultural products. China, as the world's largest importer of grain, holds an indispensable position in the international agricultural product trade market. Additionally, China is the world's largest importer of soybeans, with soybean imports accounting for approximately 90% of the annual grain import volume. During the China-U.S. trade friction period, international trade volumes of soybeans were severely affected. However, as trade relations between the two countries eased, the import and export volumes of soybeans began to gradually increase.

In the entire international trade market for agricultural dry bulks, soybeans, wheat, cotton, and corn account for the main market transaction volumes. The Chicago Board of Trade is the world's largest agricultural futures exchange, and its futures price data is more authoritative. Therefore, this paper selects the futures price index data of soybeans, wheat, cotton, and corn from January 1, 2013, to March 2024, as the objects of analysis for agricultural product market price factors.

Table2 Granger Causality Wald Tests

Equation	Excluded	Chi2	df	Prob>chi2
BDI	Corn	1.8946	2	0.388
BDI	Wheat	0.81336	2	0.666
BDI	Soybean Meal	0.1694	2	0.919
BDI	Cotton	13.769	2	0.001
BDI	ALL	19.575	8	0.012

From Table 2, it can be observed that the causal relationships between the prices of the four agricultural product futures and the BDI index vary. The p-values in the last column show that only the p-value for cotton futures is less than 0.05, allowing the rejection of the null hypothesis. This indicates a significant causal relationship between cotton prices and the BDI index. Conversely, the p-values for the other three agricultural product futures are greater than 0.05, signifying no evident causal relationship between their prices and the BDI index. Therefore, only cotton futures prices can be considered as input variables for the BDI index prediction model.

3.3 Factors Influencing Prices in the Energy Market

The impact of energy market price factors on the Baltic Dry Index (BDI) is multifaceted. On one hand, in the dry bulk energy market, key traded energy commodities include coal and timber. Among these, coal has become a relatively stable trade commodity in the international market. There is a wide variety of coal types transported as dry bulk, with coking coal and thermal coal being the most significant. Thermal coal, which is increasingly in demand for electricity generation and industrial production, is notable for its high calorific value and ability to generate significant thermal energy. Due to the concentrated distribution of coal resources, global coal mining and production are mainly centered in China, the United States, Australia, and India. Australia, often referred to as the "oasis of coal," boasts one of the largest coal reserves in the world. Australian coal not only meets domestic demand but also generates substantial revenue from exports, contributing significantly to the country's economic growth.

Timber, as a renewable energy resource, also holds a considerable share in the international dry bulk trade market. Its processing and use as an energy source contribute to environmental sustainability, further driving the growth of international timber trade. China, as the world's largest importer of timber, accounts for 25% of the international timber trade annually.

On the other hand, oil prices play an indispensable role in maritime transport. Fluctuations in international oil prices significantly impact the shipping market. As dry bulk shipping typically involves long-distance international voyages, fuel consumption is substantial. Changes in oil prices directly influence shipping costs and, consequently, the BDI. According to data from Clarkson Research, fuel costs constitute 30% to 50% of shipping transportation expenses. During the COVID-19 pandemic, international oil prices experienced dramatic volatility, which significantly affected the global shipping market. To more accurately analyze the impact of the price indices of the three energy commodities on the Baltic Dry Index (BDI), this study conducted a Granger causality test. The results of the analysis are presented in Table 3.

Table 3 Granger Causality Wald Tests

Equation	Excluded	Chi2	df	Prob>chi2
BDI	Thermal Coal Futures	14.749	2	0.001
BDI	Timber Futures	6.0796	2	0.048
BDI	WTI Crude Oil Futures	0.86021	2	0.650
BDI	ALL	22.999	6	0.001

From the table, it is evident that the significance levels of the causal relationships between thermal coal futures, timber futures, WTI crude oil futures, and the Baltic Dry Index (BDI) vary. Among the three energy commodity futures, the p-values for thermal coal and timber futures are less than 0.05, indicating a significant causal relationship with the BDI. This finding underscores the growing impact of increasing demand for thermal coal futures on the international shipping market. Consequently, the price of thermal coal futures can be considered a key input variable for predicting the BDI.

3.4 Global Economic Factors

The Baltic Dry Index (BDI), as a benchmark for international maritime trade, is closely linked to changes in the global economic landscape. Shifts in global economic conditions significantly influence international trade dynamics, which in turn impact the BDI. The status of dry bulk trade depends on the performance of the real economy and expectations for future economic activity. When the real economy performs well, international trade tends to flourish. Additionally, external market economic conditions also shape trade dynamics, thereby affecting the BDI.

Stock market indices serve as specific indicators of real economic performance and future expectations, functioning as barometers of economic trends. Among global economic indicators, U.S. stock indices are particularly influential due to Wall Street's central role in the global economy. U.S. Treasury bonds, considered a safe haven for asset allocation during economic shifts, experience significant trading volumes and are regarded as proxies for risk-free interest rates. Among the three major U.S. stock indices, the Nasdaq Composite Index and the S&P 500 Index are highly representative, encompassing stocks from diverse industries with significant influence.

For the analysis of global economic factors, this study selected the S&P 500 Index, the Nasdaq Index, and the U.S. Dollar Index as variables to assess their correlations with the BDI. All data were sourced from the Wind database. From 2013 to 2022, the Nasdaq Composite Index and the S&P 500 Index showed a steady upward trend. During the 2022 Russia-Ukraine conflict, both indices experienced a decline followed by a recovery. Despite the severe economic impact of the COVID-19 pandemic, global economic conditions improved with post-pandemic recovery, and the BDI followed a similar trajectory.

To more accurately analyze the effects of these three indices—the Nasdaq, S&P 500, and the U.S. Dollar Index—on the BDI, a Granger causality test was conducted. This analysis evaluates the causal relationships between these indices and the BDI.

Table 4 Granger Causality Wald Tests

Equation	Excluded	Chi2	df	Prob>chi2
BDI	U.S. Dollar Index	3.3913	2	0.183
BDI	Nasdaq Composite Index	2.2455	2	0.005
BDI	S&P 50 Index	1.287	2	0.525
BDI	ALL	25.353	6	0.000

In conducting the Granger causality test on global economic factors, since the time series data are stationary, the original data can be directly used for the Granger causality test. As shown in Table 4, the test results indicate that only the Nasdaq Index and the Baltic Dry Index (BDI) have p-values less than 0.05. This suggests a significant causal relationship between the Nasdaq Index and the BDI within the context of global economic factors, making them suitable input variables for the LSTM model.

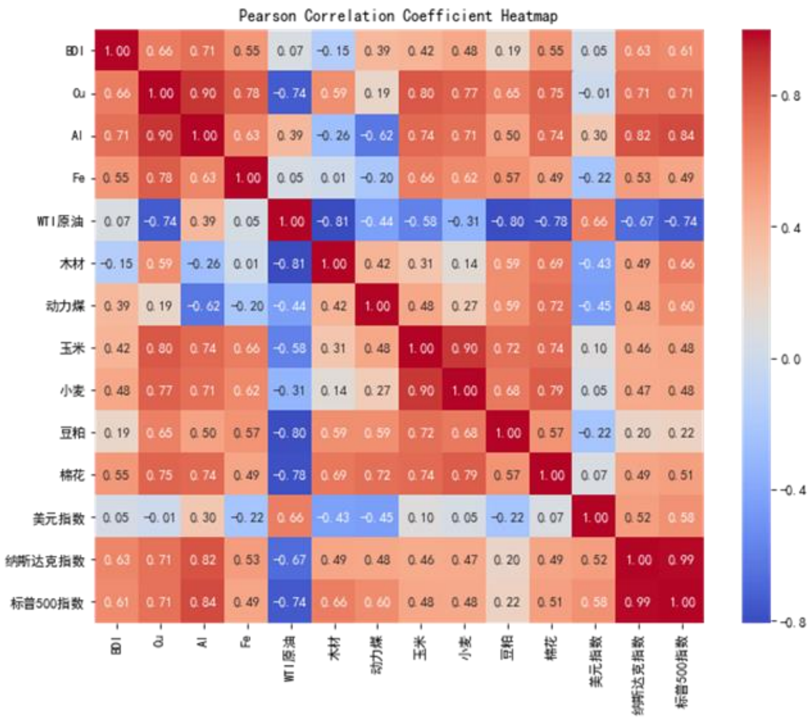
4. LSTM Neural Network Model Construction

After analyzing four key market factors, including metal market prices, agricultural product market prices, energy market prices, and global economic factors, this study reveals that the correlation between the different analysis variables and the Baltic Dry Index (BDI) varies across these factors. In order to better analyze the trends of the BDI and improve its forecasting accuracy in subsequent LSTM models, this study selects the most highly correlated indicators.

4.1 Identification of Key Determinants

These selected variables are then combined with the results from the previous Granger causality tests for further analysis and prediction. The heatmap illustrating the correlations between the BDI index and the different analysis variables across the factors is shown in Figure 4-1

Figure 4-1 Heatmap of Influencing Factors



Based on the results of the Granger causality analysis conducted earlier across the four market categories, and in conjunction with the correlation heatmap, the following conclusions can be drawn: In the metal market, since the price of Aluminum (Al) futures exhibits a Granger causality relationship with the Baltic Dry Index (BDI) and shows the highest correlation, Al futures price is selected as the first input variable for the LSTM model. In the agricultural product market, cotton futures price also demonstrates a Granger causality relationship with the BDI and has the strongest correlation, making cotton futures price the second input variable. In the energy market, the price of thermal coal futures shows a significant Granger causality relationship with the BDI and exhibits a strong correlation, thus it is chosen as the third input variable. Finally, in the global economic factors, the Nasdaq Index shows a Granger causality relationship with the BDI, with the highest correlation, so the Nasdaq Index is selected as the fourth input variable for the model.

4.2 Principle of LSTM Neural Network Models

Long Short-Term Memory (LSTM) networks, an innovative extension of Recurrent Neural Networks (RNN), were proposed by Hochreiter and Schmidhuber in 1997. The primary design goal of LSTM is to address the issues of vanishing and exploding gradients that are commonly encountered by traditional RNNs when processing long sequences of data.

4.2.1 Model Principles

The core of Long Short-Term Memory (LSTM) networks lies in their unique unit structure, which includes three primary gating mechanisms: the input gate, forget gate, and output gate. These gates collectively manage the flow of information within the unit, enabling LSTM to selectively store and modify information. This gating structure addresses the limitations of traditional Recurrent Neural Networks (RNNs), which struggle to maintain long-term memory.

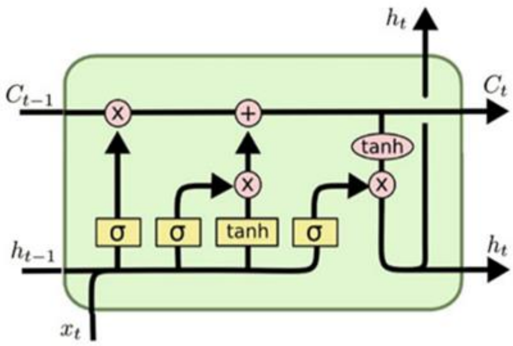
Input Gate: The input gate controls the extent to which the current input and the previous state influence the memory cell. It utilizes a Sigmoid function and a Tanh function to determine which information is important and should be retained in the cell's long-term state. The input gate allows the LSTM to capture relevant new information at each time step, facilitating the model's ability to learn from important temporal patterns.

Forget Gate: The forget gate's role is to decide which information should be discarded from the cell's internal state. By applying a Sigmoid function, the forget gate enables the model to remove data that is no longer relevant or useful for future predictions. This selective forgetting mechanism ensures that the LSTM unit remains adaptable, continuously updating its memory by removing outdated or unnecessary information.

Output Gate: The output gate determines how much information from the current cell state should be passed to the next hidden state and, ultimately, to the model's final output. This mechanism allows the LSTM to generate accurate outputs based on both the current memory cell content and the current input. The output gate plays a key role in regulating the flow of information, ensuring that relevant data is transmitted to subsequent layers of the network.

Through these three gating mechanisms, LSTM units effectively manage the flow of information, enabling them to learn and retain long-term dependencies, which is crucial for tasks involving sequential data.

Figure 4-2 Gate Control Mechanisms in the LSTM Neural Network Model



$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \tag{4.1}$$

$$i_t = \sigma(W_i \times [\mathrm{h}_{t-1}, x_t] + b_i) \tag{4.2}$$

$$\tilde{C}_t = \tanh(W_C \times [h_{t-1}, x_t] + b_C) \tag{4.3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{4.4}$$

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \tag{4.5}$$

$$h_t = o_t \times \tanh(C_t) \tag{4.6}$$

In addition to the gating mechanisms, the Long Short-Term Memory (LSTM) network introduces the concept of the memory cell (cell state), which is central to its architecture. The memory cell enables the network to retain and propagate state information across time steps, effectively addressing the problem of information loss during the processing of long sequences. The memory cell can be thought of as a highway that runs through the entire LSTM network, providing a pathway for the flow of information and helping the network maintain long-term memory.

The memory cell plays a critical role in overcoming the limitations of traditional Recurrent Neural Networks (RNNs), where the ability to remember long-term dependencies is often compromised due to vanishing gradients. By introducing a cell state that carries information across time steps, LSTM networks ensure that relevant information is retained and passed along through the sequence. At each time step, the information within the memory cell is carefully adjusted:

The input gate controls how much new information should be added to the memory cell, allowing the model to incorporate relevant data.

The forget gate determines which information should be removed from the memory cell, ensuring that outdated or irrelevant information is discarded.

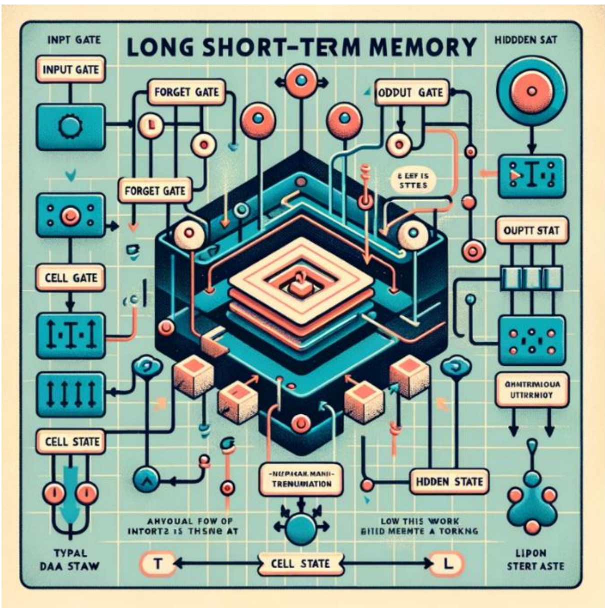
The output gate then decides how much of the current memory content should be passed to the output layer, determining the information that will influence the next hidden state and the final output.

Through these processes, the memory cell maintains the flow of information across time steps, enabling the LSTM network to capture long-term dependencies and avoid the information degradation commonly encountered in traditional RNNs. This structure is key to the model's effectiveness in tasks such as time series forecasting, language modeling, and speech recognition, where retaining contextual information over time is crucial.

From an overarching perspective, Long Short-Term Memory (LSTM) networks, with their sophisticated gating strategies and the design of memory cells, possess a highly efficient capability to capture long-term dependencies in sequential data. This research effectively addresses several challenges encountered by traditional Recurrent Neural Networks (RNNs) when processing continuous, long-duration data, such as gradient vanishing and gradient explosion. By overcoming these issues, LSTM significantly enhances the model's ability to handle long time series data and improves its generalization performance.

In practical applications, LSTM has proven to be highly successful across a wide range of sequential modeling tasks. These include, but are not limited to, language modeling, text generation, speech recognition, machine translation, and complex time series analysis. The effectiveness of LSTM in these domains demonstrates its powerful capabilities and broad application potential. Its ability to maintain long-term memory and manage the flow of information across time steps makes it an invaluable tool in areas requiring the modeling of complex temporal patterns.

Figure 4-3 LSTM (Long Short-Term Memory) Neural Network Model Structure



5. Forecast of the BDI Index

After analyzing the main factors of the BDI index, this paper establishes two types of LSTM models for predicting the BDI index. Due to the capability of the input gate in the LSTM model to handle both univariate and multivariate information, the models can be differentiated into two categories: the LSTM model with a four-factor input gate and the LSTM model with a single-factor input gate.

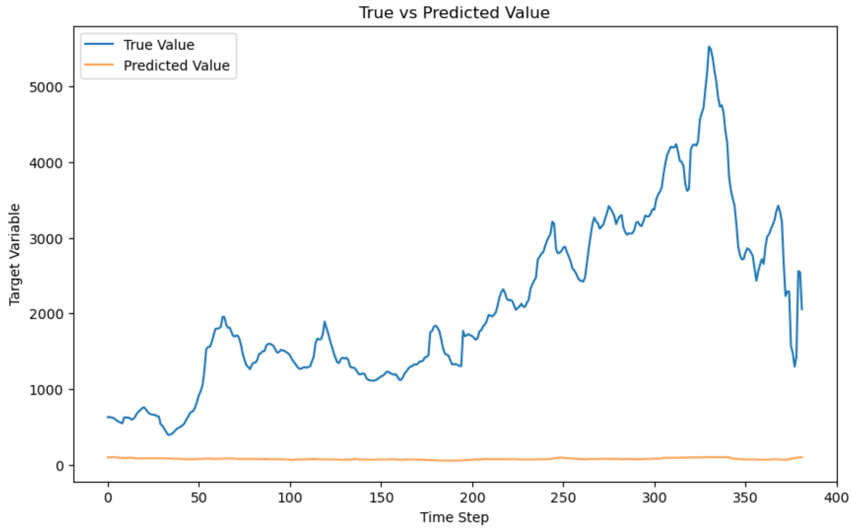
5.1 Recent Forecast of the BDI Index

The four-factor input gate model incorporates aluminum futures prices, cotton futures prices, thermal coal futures prices, and the NASDAQ index as the four variables for the input gate. In contrast, the single-factor input gate model utilizes the time series of the BDI index's price trends as the variable for the input gate.

5.1.1 Forecasting with a Four-Factor LSTM Neural Network Model

The four-factor input gate model includes aluminum futures prices, cotton futures prices, thermal coal futures prices, and the NASDAQ index as the four variables for the input gate. The final training results are depicted in Figure 5-1.

Figure 5-1 Four-Factor Prediction Model Using LSTM

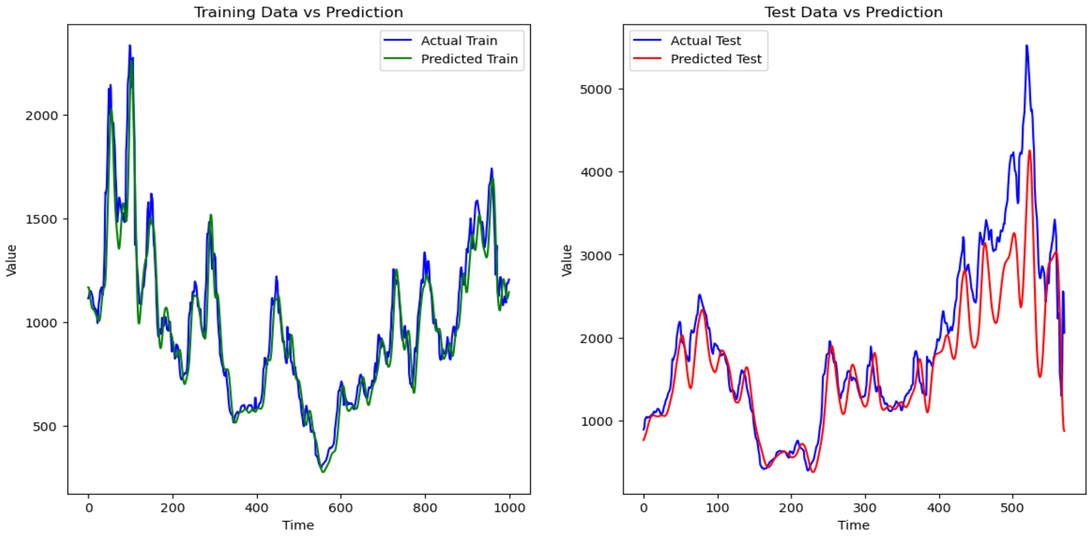


As shown in Figure 5-1, the blue curve represents the actual values, and the yellow curve represents the predicted values. From the trend, there is a significant discrepancy between the predicted and actual values. The actual values exhibit noticeable fluctuations, while the predicted values maintain an unchanging trend, resulting in excessive deviations in the curves. This indicates that the predicted values fail to provide a clear predictive effect, and the prediction accuracy is low. The reason for this situation may be the presence of correlations among different factors in the four-factor model. If these factors provide similar information or are redundant with each other, the model may struggle to distinguish their individual impacts on the BDI index. This could lead to instability in the model's fitting process or the model learning the average effect of these correlated factors rather than the independent effects of each factor.

5.1.2 Single-Factor LSTM Neural Network Model for Prediction

In the testing and training of the single-factor LSTM model, the entire training dataset is traversed by the model 10 times. Before each weight update, to enhance the model's generalization performance, gradients are calculated for the samples, and its internal parameters are updated. The final training results are presented in Figure 5-2.

Figure 5-2 Single-Factor Time Series Analysis



In the single-factor model, the input gate takes the time series of BDI index price trends as the input variable. After continuous tuning of the coefficients, the model's training and actual test set prediction results are shown in the figure above. The mean squared error (MSE) of the training set is 11,440.6, with an R2 value of 0.92, while the test set prediction results yield an MSE of 223,880.3 and an R2 value of 0.79. Based on the R2 coefficient, the model demonstrates strong explanatory power for the data and exhibits a high level of predictive performance.

From the analysis of Figure 5-2, the prediction results reflect the performance of the Long Short-Term Memory (LSTM) neural network across different time window strategies for both long-term and short-term forecasts. As shown in the figure, for long-term performance, the green curve represents the predicted values, and the blue curve represents the actual values. Comparing the predicted and actual values reveals that, although there is some deviation, the overall trends of the curves align closely. This indicates high prediction accuracy, with the primary upward and downward trends being fully captured.

For short-term performance, the red curve represents the predicted values, while the blue curve represents the actual values. The comparison shows that although the overall trend of the curves is consistent, the predicted curve exhibits more deviations. Compared to the long-term performance, the fitting degree does not show a significant advantage. However, the prediction accuracy remains relatively high.

5.2 Comparative Analysis of Single-Factor and Four-Factor LSTM Model Results

From the analysis of the above results, it is evident that the fitting degree between actual and predicted values in the four-factor model is lower, while the single-factor model demonstrates a higher fitting degree with significant predictive advantages.

5.2.1 Analysis of Causes

1. Interrelations Among Features

In the four-factor model, the various factors appear to have certain interrelationships. If these variables or information exhibit similarities or contain unnecessary redundancies, the model may struggle to clearly differentiate their individual impacts on the BDI index. Consequently, the fitting process might become unstable, with the model capturing only the average response among these factors rather than the independent effects of each.

2. Differences in Feature Importance

In the single-factor model, the LSTM focuses solely on the interaction between one specific feature and the BDI index. However, in the four-factor model, the integration of multiple features introduces complexity. Features with minimal impact on the BDI index or those containing significant noise may interfere with the model's ability to learn from the more important features, thereby reducing its accuracy.

3. Complexity of the Model vs. Dataset Size

The introduction of additional input features in the four-factor model necessitates more parameters to capture the relationships among these features. If the dataset is not sufficiently large to support this increased complexity, the model's performance may suffer. Moreover, an overly complex model may lead to overfitting, where it performs well on the training data but poorly on the test data.

4. Parameter and Structure Adjustment

For LSTM models, the configuration of parameters (e.g., the number of hidden layers and units) and hyperparameters (e.g., learning rate and optimization strategies) is crucial for achieving good fitting quality. While it is easier to identify suitable parameters and structures in the single-factor model, the adaptability of these parameters may diminish in the four-factor model, necessitating further adjustments.

5.2.2 Solutions

To address the challenges of lower fitting performance in the four-factor LSTM model compared to the single-factor model, the following optimization measures can be considered:

1. Feature Importance Evaluation

Use feature selection algorithms, such as model-based feature selection or recursive feature elimination, to evaluate the contribution of each feature to the BDI index prediction. Based on importance scores, select the top-ranked features for modeling or assign different weights to each feature.

2. Increase Dataset Size or Apply Data Augmentation

If the dataset size is limited, data augmentation techniques, such as sliding window sampling, data interpolation, or synthetic data generation, can be employed. Additionally, collecting more historical data or utilizing related data sources can help increase the number of training samples.

3. Feature Preprocessing and Engineering

(1). Normalization or Standardization: Standardize or normalize each feature to eliminate scale differences between them.

(2). Encoding Categorical Features: Convert categorical features into numerical representations using encoding techniques such as one-hot encoding or label encoding.

(3). Create Synthetic Features: Generate new features by combining or transforming existing ones to capture additional useful information.

(4). Model Simplification and Regularization

Simplify the four-factor model by reducing the number of layers or units to better match the dataset size. Regularization techniques, such as dropout or L2 regularization, can also be employed to mitigate overfitting.

4. Hyperparameter Tuning

Perform hyperparameter optimization to find the most suitable settings for learning rate, batch size, and optimizer type. This can be achieved through grid search, random search, or Bayesian optimization techniques.

5. Model Ensembling

Combine predictions from multiple single-factor models, each trained on a specific feature, to create an ensemble model. This approach can leverage the strengths of each individual model while mitigating the weaknesses of the four-factor model.

By implementing these strategies, the four-factor model can be optimized to achieve improved performance and predictive accuracy comparable to or exceeding that of the single-factor model.

6 Conclusions and outlook

This study employs the LSTM neural network model to predict the Baltic Dry Index (BDI), revealing that the single-factor model demonstrates superior predictive performance compared to the four-factor model. The single-factor model accurately forecasts the trends of the BDI, providing a deeper understanding of LSTM neural network applications in time series forecasting. Additionally, the research offers a robust theoretical foundation for investment decision-making in the shipping market.

The high precision of LSTM models in prediction enables shipping companies, traders, and investors to better comprehend market dynamics and devise more reasonable and efficient strategies for transportation and trade. Accurate predictions of the BDI not only help enterprises allocate resources more efficiently but also reduce operational costs and strengthen their competitive edge in the market. The exceptional performance of the LSTM neural network model in handling complex time series data indicates its potential for extensive applications in fields such as finance and economics.

Currently, the LSTM neural network model demonstrates impressive performance in predicting the BDI index, attributed to advancements in deep learning technology. However, there remains significant potential for further optimization and refinement of these models.

1. Integrating LSTM with Other Models；

Combining LSTM models with other deep learning architectures, such as Convolutional Neural Networks (CNN) and attention mechanisms, could improve predictive accuracy and enhance generalization performance.

2. Incorporating Additional Feature Information:

Enriching the input data by introducing more feature information can provide the model with a broader understanding of the BDI index's influencing factors. Exploring more comprehensive and relevant datasets can further reveal the patterns of BDI fluctuations and enhance prediction accuracy.

3. Advanced Optimization Techniques:

Utilizing improved optimization methods and regularization techniques can increase training efficiency and reduce overfitting. These strategies would allow the model to achieve better balance between complexity and performance.

Overall, research leveraging LSTM neural networks for BDI index prediction holds substantial practical potential and academic value. To deliver more precise forecasts for the shipping market, the following strategies can be adopted:

Continuous Model Optimization: Refining the model architecture and hyperparameters to maximize predictive performance.

Enhancing Data Accuracy: Improving data quality through better collection and preprocessing techniques.

Promoting Interdisciplinary Collaboration: Encouraging cooperation across fields such as economics, computer science, and maritime studies to integrate knowledge and achieve innovative breakthroughs.

Fostering Innovation in the Shipping Industry: Driving ongoing development through accurate predictions and informed decision-making.

Through these efforts, LSTM-based predictive research can significantly contribute to the innovation and progress of the shipping market and related industries.

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Author Contributions

Wenjie Li: Writing, Original draft, Conceptualization, Methodology. Haibo Bao: Data curation, Visualization Formal analysis, Data curation, Supervision, Validation. Xinge Lei: Conceptualization, Writing–review & editing. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials

None.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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