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Prediction of World Energy Price Index based on LSTM Model

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Abstract

In recent years, researchers have been keen to study the stock market. To better invest, many investors have focused their attention on the future trend of the stock market. With the rapid development of technology stocks, the development of energy stocks has been greatly affected, and there are few studies on energy stock price predictions. In the era of big data, traditional statistical methods are difficult to predict complex time series. Therefore, in this study, we predict world energy price index (WEPI) based on the Long Short-Term Memory (LSTM). The results show that the accuracy of LSTM predicting WEPI is 95%, the mean square error value is small, and the prediction effect is good.

Keywords

Energy; Stock Price; Prediction; LSTM; RMSE.

1. Introduction

In recent decades, the stock market has attracted many investors. Due to the large volatility of the stock market, more and more people are interested in the study of the stock market. In recent years, the rapid development of the technology industry has attracted the attention of many investors. However, the development of the energy industry is getting worse. From 1995 to 2021, the world energy price index has risen approximately 2 times, while the world information technology price index has risen approximately 15 times. Compared with other financial markets, the growth rate of energy stock prices is relatively slow, the energy industry lags far behind all other industries in the global financial market. The future development of energy has also attracted the attention of investors. Although technology stocks are booming and welcomed by investors, and the rapid development of new energy has brought a huge impact to the energy market. Oil and gas play an important role in domestic and industrial fields. The market's demand for oil is growing, so the oil and gas industry still has a certain boost behind it. Oil and gas will remain the main energy sources in the next few decades, which will ensure that it will continue to occupy an important position in the energy economy in the next few decades. The demand for energy in the global market is increasing, and non-renewable energy is becoming less and less. Energy market not only becomes a part of the financial market but also becomes a weapon for world powers to realize their financial strategic intention [1]. Affected by the 2008 financial crisis, except for the energy sector, stock prices in major industries around the world have fallen into troughs. However, energy stock prices have continued to rise. Elsayed, Ahmed H., Samia Nasreen, and Aviral Kumar Tiwari pointed out that during the financial crisis, energy stocks played an important role in constructing hedging strategies [2]. In a bull market, energy stocks have always performed poorly. However, in a bear market, energy stocks play a very important role in the study of hedging strategies. It is very important to seize the investment opportunities in the energy stock market with time-varying co-movement. Therefore, we can predict the trend of energy stock price to provide reference for investment strategies.

The amount of stock data is large, and it is difficult for traditional statistics methods to predict the time series of a large sample. Due to the large volatility of the stock market, multiple financial time series are complex non-linear models, and traditional statistical methods are difficult to predict the

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trend of stock prices. Due to the rapid development of artificial intelligence, deep learning has excellent nonlinear modeling capabilities and has good predictive ability for large-scale financial time series. Recurrent neural networks (RNN) have proved one of the most powerful models for processing sequential data [3]. The proposal of long and short-term memory solves the gradient problem of recurrent neural networks, and the prediction accuracy of long-term and short-term memory is relatively high. Therefore, this study considers long and short-term memory method to predict the world energy price index. Improving the prediction accuracy of world energy price index can enable investors to better understand the development trend of energy stocks and provide investors with decision-making reference.

2. Methodology

2.1 Data Processing

First, we collect historical stock data from the wind database. These historical data are used to predict future stock prices. Then, we proceed to the most important step: normalization. Normalization allows features between different dimensions to be numerically comparable and improves the accuracy of model predictions.

The formula for data normalization is as follows (1):

$$x^* = \frac{x - \min}{\max - \min} \tag{1}$$

The formula is to perform a linear transformation on the original data, so that the result of the original data falls into the interval [0,1]. Where x is the original data, x* is the standardized data, max is the maximum value of the sample data, and min is the minimum value of the sample data.

Next, we fill in the missing values in the data set. Finally, we divide the data set. The first 80% rows of historical data are used as the training set, and the last 20% rows of the data are used as the test set.

2.2 Long Short-Term Memory

Long Short-Term Memory proposed by Hochreiter, Sepp, and Jürgen Schmidhuber. (1997) [4] is considered in this paper to predict world energy stock price index. The prediction of market value is helpful for maximizing profits while keeping risks low. Fischer, Thomas, and Christopher Krauss proved that the LSTM network can effectively obtain useful information in complex financial time series data [5]. Therefore, LSTM is considered in this study.

The structure of Long Short-Term Memory Network is shown in the figure1 below:

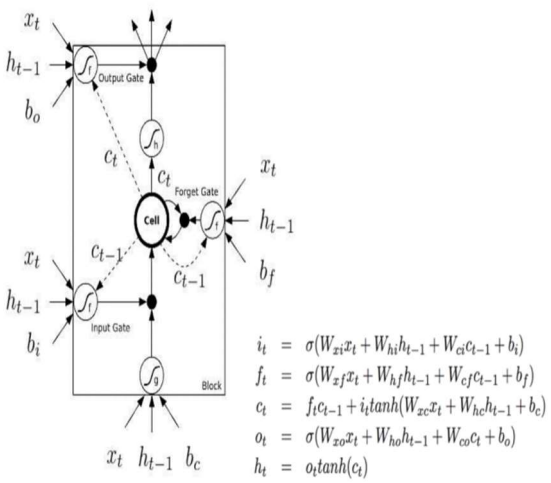

Figure 1. The structure Long Short-Term Memory

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Where t is the time step, xt and ht are the input and output vectors of the hidden layer of the LSTM, and ct is the memory cell. f is the forget gate, i is the input gate, o is the output gate. W and b represent the weight matrix and bias vector in the network. σ and tanh are activation functions. In the LSTM model, a suitable activation function can be selected according to the needs of the research.

Long Short-Term Memory Network Architecture refer to this article [6].

In this study, the model consists of two LSTM layers and a dense layer. The first LSTM layer is composed of 64 neurons, and the second LSTM layer is composed of 32 neurons The code to implement the Neural Network model is shown in the Figure 2 below:

```
model=tf.keras.models.Sequential()
model.add(LSTM(64, input_shape=(train_X.shape[1],
                                train_X.shape[2]),
               return_sequences=True))
model.add(Dropout(0.1))
model.add(LSTM(32,return_sequences=False))
model.add(Dropout(0.1))
model.add(Dense(1,activation='relu'))
```

Figure 2. The code of the Neural Network

3. Analysis

To analyze the efficiency of this model, we use the root mean square error (RMSE) as the analysis index. In this study, our goal is to minimize the RMSE value. RMSE is the square root of the sum of squares of the deviation of the predicted value from the true value and the ratio of the number of predictions n. It represents the deviation of the measured value from the observed value and is a widely used analysis indicator.

The formula of RMSE is as follows (2):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{2}$$

Where n is the number of samples, ei is the difference between the true value and the observation value of the i-th sample. Minimizing the RMSE value is the goal of this research. The smaller the RMSE value is, the better the prediction effect is.

In addition, we also calculated other evaluation indicators in the experiment, such as: Mean Absolute Error (MAE), coefficient of determination. MAE represents the average value of the absolute error between the predicted value and the observed value. The coefficient of determination reflects the reliability of the dependent variable changes in the model.

4. Experimental Work

4.1 Data Set

In this study, we consider the daily closing prices data of MSCI World Energy Price Index (WEPI), MSCI World Market Price Index (WMPI), MSCI World Stock Price Index (WSPI), MSCI World Financial Price Index (WFPI), MSCI World Utility Price Index (WUPI), MSCI World Raw Material Price Index (WRMPI), MSCI World Daily Consumer Price Index (WDCPI), MSCI World Non-Daily Consumer Price Index (WNDCPI), MSCI World Information Technology Price Index (WITPI). The MSCI index is widely adopted by global portfolio managers and has considerable international influence. The data ranges from 30.12.1994 to 31.3.2021 and are collected from Wind database. In the above index prices, WSPI and WMPI consider the impact of the overall global market price index on WEPI, and the remaining six indexes consider the impact of other industries on WEPI.

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In addition to the impact of other price indexes, we also consider the impact of the closing price of WEPI and the technical indicator MACD. We used its closing price to calculate the technical indicator Moving Average Convergence and Divergence (MACD). In the stock market, there are many commonly used technical indicators, MACD is a very classic technical indicator. The change of MACD indicates the change of financial market trend. The buying and selling trend of different K-line levels in the current horizontal cycle can be expressed by MACD.

There are ten features in this model, namely: WEPI; WMPI; WSPI; WFPI; WUPI; WRMPI; WDCPI; WNDCPI; WITPI; MACD. We got 6608 sequences from 30.12.1994 to 31.3.2021. In these data sets, 5286 samples are used for training and 1322 samples are used for verification.

4.2 Parameters of Experiment

In this study, we predict WEPI based on the learning environment of keras (frontend) and tensorflow (backend). The activation function we chose is Rectified Linear Units (Relu). Relu overcomes the problem of gradient disappearance and speeds up training. To prevent over-fitting problems, this article adds a Dropout layer. Dropout randomly disconnects the connections between neural networks, reducing the number of parameters of the model involved in the calculation during each training, thereby reducing the actual capacity of the model to prevent overfitting. To train this model, since Nadam has stronger constraints on the learning rate, we use Nadam as the optimizer and normalize the order of each vector. The number of iterations of the training process is 100. The batch_size of the model is equal to 64, which means that the number of samples selected for one training is 64.

5. Experimetal Results

In the neural network model, as the training epoch increases, the training loss and test loss decrease. Compared with the loss value of the training set, the loss value of the test set is larger at the beginning. After several rounds of testing, the loss value of the test set gradually decreases. It converges fast and gradually become flat from the 30th epoch. After 100 epochs of training, the loss value is about 0.001. The loss value of the model is shown in Figure 3.

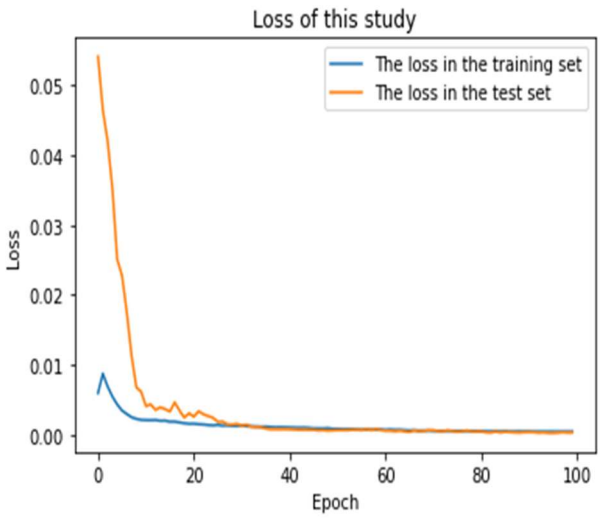

Figure 3. The loss value of the model

The experimental results show that the coefficient of determination of the model is 0.952. It shows that all the explanatory variables we have included in the model have a higher degree of influence on the combination of dependent variables. The results show that the root mean square error of this experiment is 6.07, the mean absolute error is 4.93. These results show that the forecasting effect of this time series is good. In the test set, we can find that the similarity between the predicted value and the original value is very high. The predicted result in the model is shown in Figure 4.

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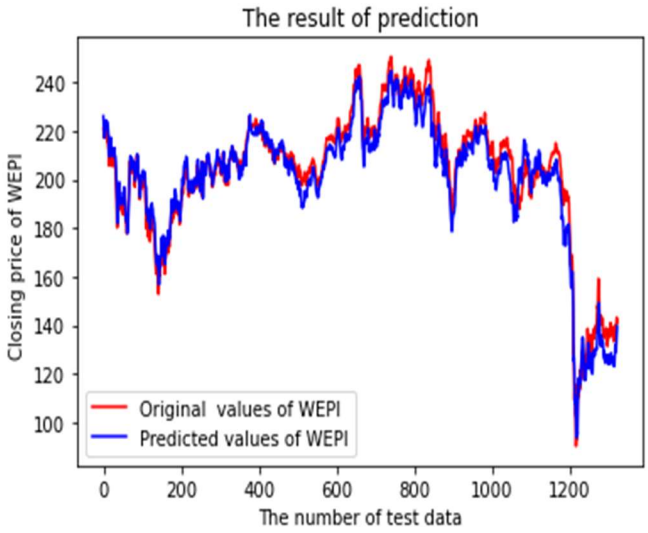

Figure 4. The predicted result in the model

6. Conclusion

This paper applies deep learning theory, based on the characteristics of multiple financial time series data, and uses LSTM to predict the world energy price index. The experimental results show that Long and Short-Term Memory performs better on the test set. However, LSTM is not a reliable model that can perfectly predict stock trends. The research in this article is only for learning, not stock trading.

This study only considers the impact of stock price indicators in different industries and a single technical indicator on the global energy price index and does not consider the impact of stock price indexes in different regions. In addition, this study does not consider the impact of current events, policies, and other influencing factors on the world energy price index. In addition, the financial market is relatively volatile and extremely vulnerable to emergencies. Over the past year, many industries have been affected by Corona Virus Disease 2019 (COVID-19). Therefore, it is difficult to find all influencing factors in the study of stock price trend forecasting.

This study believes that LSTM has a better predictive effect on energy stock prices. However, the hyperparameters of the model will significantly affect the training results, such as the learning speed of the optimizer, the number of network layers, the number of hidden nodes in each layer, the optimizer, and so on. It is difficult for us to find the most suitable hyperparameters for the model. Therefore, to improve the prediction accuracy of the model, we must constantly change the hyperparameters in the process of training the model by finding more suitable hyperparameters.

Energy is everywhere and occupies a very important position. In the existing research, Crude oil, electricity prices and energy demand are popular studies in the energy sector, there are few studies on energy stock prices, so it is very necessary to study energy stock prices. With the growth of technology stocks, many investors are keen to invest in technology stocks and neglect the research on energy stocks in the financial market. Existing studies have shown that energy stock is of great significance in the study of hedging strategies. Therefore, it is very necessary to study energy stock in the construction of investment strategies. However, because the financial market is affected by many factors and changes instantaneously, to obtain better investment returns, it is necessary to consider the impact of multiple factors on stock prices.

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