

# A Stock Index Prediction Model Based on LSTM: Taking New Energy Vehicles as an Example

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**Abstract:** Stock indices can partially reflect the overall price level and variations of various stocks in the market. Therefore, analyzing the stock index of new energy vehicles aids in predicting future market trends. However, stock prices, as time series data, display traits of nonlinearity and high noise. This study proposes employing the denoising method of Singular Spectrum Analysis (SSA) on the CNI New Energy Vehicles Index (399417) and constructing an SSA-LSTM model. Comparative results with a single LSTM model demonstrate that the evaluation indicators  $R^2$  of the SSA-LSTM model increase by 0.06, RMSE decreases by 54.37, and MAE decreases by 49.49. These findings suggest that SSA can enhance the predictive accuracy of the model.

**Keywords:** Singular Spectrum Analysis; Long Short-Term Memory; Stock Index Prediction.

## 1. Introduction

Driven by the green development strategy and the promotion of low-carbon economy, new energy vehicles have represented the general trend in industrial development and a pivotal aspect of automotive industry transformation. Simultaneously, the stock market, as an integral part of the market economy, has long been a primary focus for scholars around the world in terms of predicting stock index prices. This not only aids investors in comprehending the performance of stock prices in relevant sectors but also offers insights into national policies. Despite the growing significance of the new energy vehicle industry, research has focused primarily on vehicle performance and policy initiatives, with limited attention paid to the prediction of stock indices.

Long Short-Term Memory (LSTM) represents a distinct form of recurrent neural networks (RNN) which efficiently address the challenges of gradient vanishing and exploding. Moreover, LSTM resolves the prevalent problem of long-term dependency in conventional neural networks, making it well-suited for managing non-linear and highly noisy time series data.

Singular Spectrum Analysis (SSA) is a methodology employed for examining non-linear time series data. It involves decomposing and reconstructing the trajectory matrix of the time series to extract various component sequences, such as noise, long-term trends, and seasonal trends. Nevertheless, SSA is currently underutilized in financial research.

This paper aims to employ Singular Spectrum Analysis to denoise the original time data and integrate it with an LSTM model for data prediction. Ultimately, an evaluation of the prediction outcomes will be conducted.

## 2. Literature Review

In recent years, there has been a significant attention towards energy-related issues and the concept of a low-carbon economy. The transportation sector, ranking as the world's second-largest emitter of carbon, has contributed to

substantial depletion of resources and environmental contamination challenges. The automotive industry faces a dilemma as it heavily relies on petroleum and simultaneously expands. To effectively tackle escalating global climate issues and expedite the shift towards a green and low-carbon society, countries worldwide are endorsing new energy vehicles as a national strategy for cultivating low-carbon transportation.

New energy vehicles play a crucial role in the global energy governance by reducing energy costs and mitigating greenhouse gas emissions. Thus offering countries a significant pathway to achieve development of clean energy and renewable energy [1,2]. These vehicles are now the primary focus of the automotive industry's transformation worldwide, acting as a key driver for sustained global economic growth. The development of new energy vehicles represents a strategic response to climate change and the promotion of sustainable green practices. In recent years, extensive research has been conducted domestically and internationally in this field, with a predominant focus on power batteries [3,4], government subsidies [5], strategic studies [6,7], and optimization of charging infrastructure [8]. Notably, there remains a research gap in the prediction of stock prices for new energy vehicle companies. Despite the significance of stocks in facilitating financing, risk management, and policy development for such enterprises, investors consider stock price prediction as a crucial factor for generating profits and avoiding risks. Hence, conducting research on the stock price predictions in the context of new energy vehicle industry holds immense importance.

The stock market, as a crucial component of the market economy, consistently garners considerable attention due to its trends. As artificial intelligence and big data technologies continue to advance rapidly, the field of stock market prediction has gained widespread recognition and interest.

Traditional stock forecasting models rely significantly on mathematical statistics for researching and forecasting. In their study, Yuxia Wu and Xin Wen analyzed and forecasted price fluctuations of Huatai Securities, a listed stock on the ChiNext board, by using the ARIMA model. Remarkably, they achieved favorable outcomes in short-term price prediction [9]. Similarly, in the analysis of the stock price of

Shanghai Dazhong Public Utilities (600635), Qi Yang and Xianbing Cao found that ARMA-GARCH model has a high accuracy in its prediction [10]. Despite the fact that conventional stock prediction models exhibit relatively dependable forecasting capabilities for short-term fluctuations in stock prices, it is important to acknowledge that they face significant limitations. The stock price data has the characteristics of nonlinearity, high noise, complexity, and vulnerability to the impact of national policies.

With the emergence of the big data era, machine learning methods have been employed in forecasting stock prices. Specifically, the Backpropagation [11], support vector machine [12,13], and random forest [14] have been utilized in this field. For error reduction and improvement of accuracy, Guisheng Zhang and Xindong Zhang introduced the SVM-GARCH model for forecasting the Nikkei 225 stock index and proved that the superiority of this model over the conventional ARMA-GARCH model [15]. Moreover, Jihong Xiao, Xuehong Zhu, Chuangxia Huang et al. developed a new method that integrates SSA with SVM for stock prediction [16]. Additionally, Fangzhong Qi, Shaoqian Lin and Tingting Yu devised the PCA-IFOA-BP stock price prediction model, which exhibits superior accuracy compared to the Backpropagation, PCA-BP, and PCA-FOA-BP [17].

The progress of computer capabilities has resulted in a widespread application of deep learning algorithms possessing highly improved predictive abilities in predicting financial sequence data. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) are some of the algorithms used in various studies. Currently, an increasing number of researchers aspire to achieve breakthroughs in the area of stock prediction through the utilization of deep learning techniques. Yan Peng, Yuhong Liu and Rongfen Zhang conducted experiments involving LSTM models with varying layers and hidden neurons. They determined that the optimal configuration was comprised of 2 layers and 10 neurons [18]. Xiaojian Yu, Guopeng Liu, Jianlin Liu et al. conducted an analysis of text data from individual stock comments, extracted market sentiment features, and incorporated them with LSTM to predict stock prices [19]. Furthermore, there has been a recent application of mixed deep learning models in the domain of stock forecasting. Several scholars integrated LSTM and CNN models for the purpose of predicting stock prices by employing time series data and stock images [20,21]. Bowen Cai conducted a comparative analysis of economic predictions in the new energy vehicle industry by utilizing financial information derived from annual reports. The findings revealed that the fusion model of CNN and GRU demonstrated the most superior combination property [22]. Zexin Hu, Yiqi Zhao and Matloob Khushi conducted a comprehensive research analysis on the utilization of diverse deep learning methods on the part of financial prediction. The findings revealed that models combining LSTM with other methods exhibited superior performance [23]. Zaheer Shahzad, Nadeem Anjum, Saddam Hussain et al. conducted a comparative analysis of prediction results from multiple hybrid deep learning models on stock parameters, specifically close price and high price [24].

Simultaneously, Singular Spectrum Analysis (SSA), which is a robust technique used for time series analysis, has been widely employed to address a multitude of practical problems. Hossein Hassani utilized SSA on a renowned dataset containing monthly accidental deaths rates in the United

States, and observed a significantly higher level of accuracy in forecasting compared to other methods [25]. Cong Wang, Hongli Zhang and Ping Ma combine Singular Spectrum Analysis with a hybrid Laguerre neural network to forecast future wind power values [26]. Kutubuddin Ansari, Sampad Kumar Panda and Punyawi Jamjareegulgarn found that the SSA method can be a predictive tool for Total Electron Content (TEC) sequences in the region of Nepal [27].

## 3. Methodology

### 3.1. Singular Spectrum Analysis (SSA)

Singular Spectrum Analysis (SSA) is a robust method utilized for time series analysis, initially proposed by Colebrook in 1978. The aim of this method is the decomposition of the original sequence into components that contain information which is independent of each other. The key steps of SSA include the following four:

#### 3.1.1. Embedding

Consider a one-dimensional time series  $Y_N$ , represented by  $\{y_1, y_2, \dots, y_N\}$ , with a length of  $N$ . To obtain the trajectory matrix  $X$ , the one-dimensional time series is transformed into a multi-dimensional sequence by selecting a suitable window length  $L$ . The resulting trajectory matrix is as follows:

$$X = \begin{bmatrix} y_1 & y_2 & y_3 & \dots & y_K \\ y_2 & y_3 & y_4 & \dots & y_{K+1} \\ y_3 & y_4 & y_5 & \dots & y_{K+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & y_{L+2} & \dots & y_N \end{bmatrix} \quad (1)$$

Among these parameters, it is standard to select a window length  $L$  that typically falls in the range of  $2 < L < N/2$ , where  $K = N - L + 1$ .

#### 3.1.2. Singular Value Decomposition (SVD)

The next step is use SVD to process the trajectory matrix, decomposing it into the following format:

$$X = U\Sigma V^T \quad (2)$$

In the above equation,  $U$  represents the left singular matrix of  $L \times L$ , and its orthogonal vectors are known as the left singular vectors.  $\Sigma$  is the singular value diagonal matrix of  $L \times K$ , where all non-diagonal elements are 0. The singular values, denoted as  $\Sigma = [\lambda_1, \lambda_2, \dots, \lambda_L]$ , are the elements on the diagonal that satisfy  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_L \geq 0$ .  $V$  represents the  $K \times K$  right singular matrix, and its orthogonal vectors are called the right singular vectors. Subsequently, the singular entropy theory is employed for noise extraction.

Entropy is a fundamental concept in information theory, essential for quantifying the amount of information in a message. In order to separate the noise information from stock price time series, the concept of singular entropy has been introduced to determine the order of the reconstructed sequence obtained through singular value decomposition (SVD). The calculation formula for singular entropy and its increment is presented below.

$$E_k = \sum_{i=1}^k \Delta E_i, \quad k \leq m \quad (3)$$

$$\Delta E_i = -\frac{\sqrt{\lambda_i}}{\sum_{i=1}^L \sqrt{\lambda_i}} \log \frac{\sqrt{\lambda_i}}{\sum_{i=1}^L \sqrt{\lambda_i}} \quad (4)$$

According to the theory of singular entropy, if the decrement of the singular value increment  $\Delta E_i$  tends to stabilize when the singular values reach the  $k$ th order, it suggests that the meaningful information is widely enclosed within the singular values from order one to  $k$ .

### 3.1.3. Grouping

Group the singular values in  $\Sigma$  based on their magnitude. Larger singular values correspond to signal components, while smaller ones are associated with noise. If the singular values' extraction is predetermined with  $k$ , the resulting grouping is denoted as, where  $X = X_1 + X_2 + \dots + X_k$ , where  $X_i = \sqrt{\lambda_i} U_i V_i^T$ .

### 3.1.4. Reconstruction

The previous matrix is converted into a one-dimensional sequence with a length of  $N$  through diagonal averaging. Let  $T \in R^{L \times K}$  represents the matrix, where  $T_{i,j}$  indicates the element at position  $(i,j)$  in the matrix, corresponding to the element located in the  $i$ th row and  $j$ th column. The indices are subject to the conditions  $1 \leq i \leq L$  and  $1 \leq j \leq K$ . The matrix  $T$  undergoes a transformation into a one-dimensional time series of length  $N$  through diagonal averaging by defining  $K^* = \max(L, K)$  and  $L^* = \min(L, K)$ , denoted as  $t_1, t_2, \dots, t_N$ . The reconstructed sequence can be calculated using the following formula:

$$t_k = \begin{cases} \frac{1}{k} \sum_{m=1}^k T_{m,k-m+1}, & 1 \leq k \leq L^* \\ \frac{-1}{L^*} \sum_{m=1}^{L^*} T_{m,k-m+1}, & L^* \leq k \leq K^* \\ \frac{1}{N-k+1} \sum_{k-K^*+1}^{N-K^*+1} T_{m,k-m+1}, & K^* < k \leq N \end{cases} \quad (5)$$

## 3.2. Long Short-Term Memory(LSTM)

LSTM (Long Short-Term Memory) is a type of recurrent neural network specifically designed for processing sequential data and capturing past information. A basic LSTM unit consists of a cell and three gates: an input, output and forget gate. The flow of information through LSTM is regulated by the three gates, or gate mechanisms, which enables LSTM to handle lengthy sequential data efficiently. Figure 1 provides a detailed depiction of the structure.

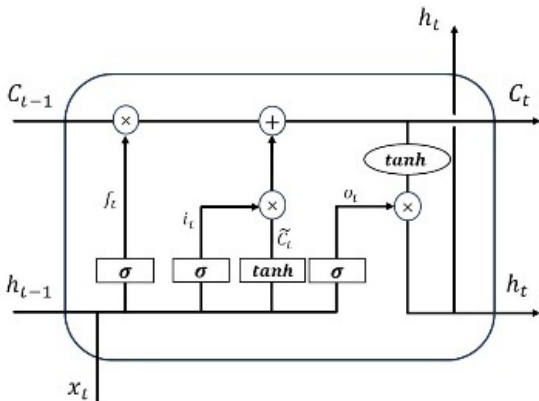


Figure 1. LSTM network structure

The forget gate in LSTM regulates the selective forgetting of information within the cell state. At time  $t$ , by using the Sigmoid function to assess the input signal  $x_t$  and the output signal  $h_{t-1}$  from time  $t-1$ , the evaluation leads to the

attainment of a value ranging from 0 to 1. In this context, 0 signifies complete forgetting, while 1 indicates complete retention. The below formula provides the specific calculation.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (6)$$

The input gate of the LSTM is of paramount importance in determining what proportion of input information to store in the current state. By taking  $x_t$  and  $h_{t-1}$  as inputs, the Sigmoid function generates  $i_t$  as an output. In addition, the tanh function integrates the inputs  $x_t$  and  $h_{t-1}$  to form a candidate cell state  $\tilde{C}_t$ . The cell state  $C_t$  is updated based on  $i_t$  and  $\tilde{C}_t$ . The following specific formulas show the update of  $C_t$  at time step  $t$ :

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (7)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (8)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (9)$$

The output gate determines the output value  $h_t$  by taking into account  $C_t$ . The output gate combines the current input signal  $x_t$  with the cell state  $C_{t-1}$  and the previous output signal  $h_{t-1}$  from time step  $t-1$  to generate the present output signal. The input signal  $x_t$  and previous output  $h_{t-1}$  are passed through the sigmoid function, resulting in a value  $o_t$ , which falls within the range of 0 to 1. To obtain an output signal  $h_t$ , the cell state  $C_t$  is processed by the tanh function, yielding a value within the interval of  $[-1,1]$ , and then multiplied by  $o_t$ . Furthermore,  $h_t$  is propagated as the input signal for the subsequent time step, initiating further processing. The calculation formulas for  $h_t$  are as follows.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (10)$$

$$h_t = o_t * \tanh(C_t) \quad (11)$$

## 4. Empirical Analysis

### 4.1. Experimental data

#### 4.1.1. Data sources

This paper employed information on CNI New Energy Vehicles Index (399417) spanning from 1 July 2013 to 30 June 2023. The dataset comprises information on opening, closing, lowest and highest prices, as well as trading volumes and price variations, totaling 2425 data points.

#### 4.1.2. Data preprocessing

The raw data obtained may contain issues such as missing values, disorder, and inconsistent formatting. Consequently, preprocessing the raw data becomes imperative, entailing tasks such as handling missing values, sorting, and adjusting data formats. These operations are undertaken to acquire a standardized dataset.

### 4.2. Data denoising and normalization

Raw time series data of stocks frequently includes data noise, which may impact the convergence speed of data, model accuracy, and prediction effectiveness. In order to tackle this matter, this study utilizes the Singular Spectrum Analysis (SSA) for data denoising.

#### 4.2.1. Selection of window length $L$

The selection of an appropriate window length is important

in SSA as it directly impacts the effectiveness of the analysis and the resulting decomposition. In a time series of length  $N$ , the window length need not surpass  $N/2$ . Moreover, a lengthier window length  $L$  leads to a more detailed decomposition of the sequence. Conversely, if  $L$  is too small, it impedes the extraction of components [28]. To determine the appropriate window length, this study empirically selects a value of 1200. Additionally, the incremental values of each singular value are computed using singular entropy. The change in the increment of the singular entropy is shown in Figure 2.

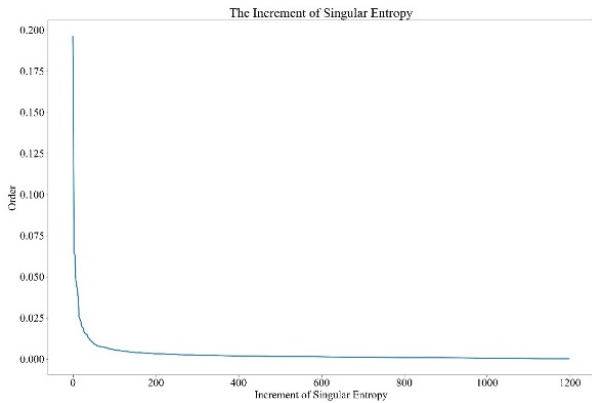


Figure 2. The variation of the singular entropy increment

#### 4.2.2. Order selection for singular value reconstruction sequences

From the data presented in Figure 2, it is evident that the increment of the singular values stabilizes when the order reaches 300. Therefore, this paper proposes selecting the singular value reconstruction sequence up to the 300th order.

#### 4.2.3. Normalization

To remove the influence of dimensionality among indicators, normalization of the feature sequence is required, which involves mapping it onto the interval  $[0,1]$ .

### 4.3. Experimental results and analysis

This article compares experimental results for assessing model accuracy and prediction precision by using the evaluation metrics of coefficient of determination ( $R^2$ ), root mean square error (RMSE) and mean absolute error (MAE). A smaller RMSE and MAE value signifies a smaller error and improved prediction performance. The calculation formulas are as given below.

$$RMSE = \left( \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \right)^{1/2} \quad (12)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (13)$$

The values of  $R^2$  vary between 0 and 1. The model's fit and prediction performance improve as the  $R^2$  value approaches 1. The calculation formula is presented below.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (14)$$

This experiment employs the LSTM, comprising two LSTM layers and one Dense layer, with a configuration of 10

hidden neurons. The model is set with specific parameters: batch\_size of 32, 50 epochs, and a division of the data into training and testing sets at an 8:2 ratio. The predictions are performed separately on the data subjected to SSA and the original non-processed data. Figure 3 and Figure 4 respectively show the experimental outcomes of the SSA-LSTM model and the LSTM model.

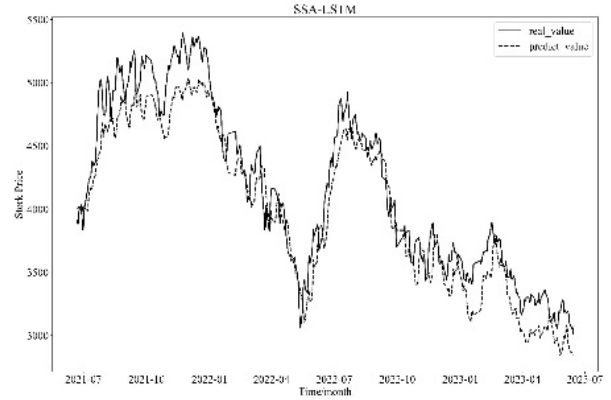


Figure 3. Results of SSA-LSTM model predictions

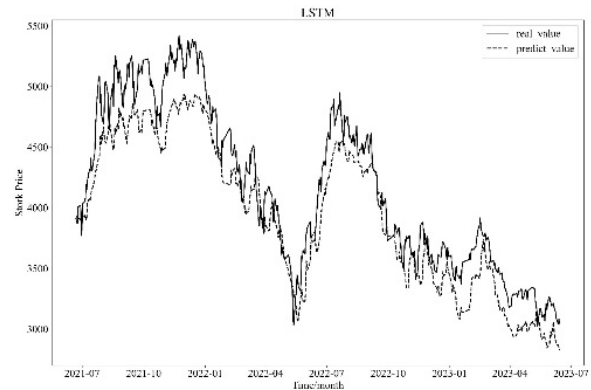


Figure 4. Results of LSTM model predictions

The evaluation metrics for the two models were calculated individually, and Table 1 presents the corresponding results below.

Table 1. Comparison of evaluation metrics for SSA-LSTM model and LSTM model

	$R^2$	RMSE	MAE
LSTM	0.82	281.62	241.75
SSA-LSTM	0.88	227.25	192.26

Table 1 displays the findings which indicate that the SSA-LSTM model reduces the RMSE and MAE by 54.37 and 49.49, respectively, in comparison to the LSTM model. Additionally, the  $R^2$  increases by 0.06. These results demonstrate the superior capability of the LSTM model for forecasting financial time series data, particularly in predicting stock prices. Moreover, the results suggest that SSA enhances the extraction of more relevant data, leading to an improved accuracy of the predictions.

## 5. Conclusion

Given the intricacy and unpredictability of the stock market, this study suggests a blended approach that combines SSA with LSTM to enhance the analysis and prediction of stock prices. The chosen dataset for this research comprises the CNI

New Energy Vehicles Index (399417), which reasonably reflects the general level and fluctuations of stock market prices in the broader new energy vehicle stock market. Following preprocessing steps involving SSA denoising and normalization techniques, the SSA-LSTM model is developed for the analysis and prediction of the price of the CNI New Energy Vehicles Index (399417), subsequently comparing it against the LSTM model. The findings demonstrate that incorporating SSA effectively enhances the prediction accuracy of the LSTM model.

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