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LSTM Networks' Multi-Feature Stock Price Prediction using VMD and TMFG

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Traditional approaches find it challenging to represent the stock market's complex dynamics and nonlinear properties due to its high levels of nonlinearity and complexity. The goal of this study is to improve prediction accuracy, stability, and computing efficiency by introducing a unique stock price forecasting model called the VMD-TMFG-LSTM combination model. In order to minimise noise interference and simplify the data, the stock price time series are first broken down into a number of smooth intrinsic mode functions (IMFs) using variational mode decomposition (VMD). For feature selection, an information filtering network (TMFG) algorithm is then used, which further streamlines the input data and speeds up the iterative convergence process. Ultimately, a long short-term memory (LSTM) network is used to model and forecast the filtered features. The VMD-TMFG-LSTM model outperforms the single LSTM, TMFG-LSTM, and VMD-LSTM models in terms of prediction accuracy and operational efficiency when it comes to predicting the closing prices of different equities, according to experimental results. Ultimately, the combination model presented in this research offers substantial stability and robustness while greatly improving stock price forecast accuracy and efficiency.

Keywords: VMD, TMFG, LSTM, stock price prediction.

1. Introduction

Stock forecasting is the process of predicting future patterns in stock prices by examining past stock market data. The stock market is regarded as one of the most intricate financial systems due to its extremely complicated and nonlinear character [1]. For investors and market analysts, stock forecasting is a technique that uses historical data from the stock market to predict future price movements. It has both theoretical and practical significance. Even while they excel at handling linear data, traditional statistical techniques like moving averages, exponential smoothing [2], and ARIMA models [3] frequently find it difficult to capture the complex market dynamics and non-linear elements seen in the stock market. The quick development of artificial intelligence technologies, particularly deep learning, has led to a revolution in stock prediction techniques. A specific Recurrent Neural Network (RNN) called Long Short-Term Memory (LSTM) [4] has emerged as a potent instrument for handling time series data.Through its unique gating mechanism, LSTM successfully addresses the issue of gradient vanishing that traditional RNNs face when processing lengthy time series data. This allows LSTM to recognise and take advantage of long-term dependencies in the data, significantly improving the model's accuracy for time series prediction.

Accurately predicting stock prices is still very difficult, though, due to the stock market's extreme volatility, nonlinearity, chaos, and operational complexity. This study suggests a state-of-the-art combinatorial model (VMD-TMFG-LSTM) that combines the LSTM network, information filtering network (TMFG algorithm), and variational modal decomposition (VMD) in order to successfully solve these issues. In order to simplify the data and successfully eliminate unstructured noise, this model begins with an accurate decomposition of stock closing price series using the VMD technique. The TMFG method then sparsely dimensionalizes the processed data, which not only lessens the processing load but also identifies the key characteristics that affect stock price fluctuations. In order to accomplish accurate stock price prediction, the filtered important characteristics are then supplied into the LSTM network for deep training.

Combining these techniques results in a current model that not only dramatically advances our understanding of stock market dynamics but also greatly increases the model's stability and applicability due to its excellent prediction capacity and high adaptability to new data. In order to solve the problem of stock price prediction with high volatility, nonlinearity, and chaos, as well as to improve prediction accuracy and efficiency, this paper innovates by combining the information filtering network (TMFG algorithm) with variational modal decomposition (VMD) and LSTM. Furthermore, the creation of this model offers fresh avenues for financial technology research and solutions.

The following are the study's innovations and contributions:

(1) The stock price data is used to generate the technical indicators of the stock. 43 technical indicators are also calculated, and when combined with the 16 indicators that were previously present in the original data, the indicators reach 59 characteristics. The stock price prediction indicator system has been enhanced.

(2) VMD modal decomposition is applied to the closing price. The stock price time series is broken down into several smooth IMF components by the VMD algorithm, which increases prediction accuracy and lessens test error noise interference.

(3) By using the TMFG algorithm to choose the input features, the input becomes less complex, the iterative convergence speed and error are accelerated, and the prediction's stability and robustness are increased.

The remainder of the document is structured as follows: The second section, the literature review, gives a summary of current stock prediction models and techniques, talks about feature selection and data decomposition, and presents the use of LSTM for stock prediction and the TMFG algorithm for filtered data. The third section, Methods and Data, covers the TMFG method, the LSTM network, and the fundamentals of VMD decomposition. It also explains how the combined VMD-TMFG-LSTM model was built. It also explains the study's data sources and preprocessing. The experimental procedure and findings of VMD decomposition, TMFG processing, and LSTM prediction are presented in the fourth section, which also compares the models' prediction effects. The fifth section is the summary, which will provide an overview of the model's benefits and study findings while also going over the model's drawbacks and potential future research areas.

2. Literature Review

Zhang, Y., et al. (2019) [5], Presented an LSTM-based model integrated with VMD for decomposing financial time series into distinct frequency components. The VMD process enhances signal quality and reduces noise, allowing LSTM to predict with higher accuracy. Demonstrated improved performance in multi-step forecasting for volatile markets.

Chen, J., and Huang, L. (2020) [6], Proposed a TMFG-enhanced feature selection method combined with LSTM for stock price forecasting. TMFG identifies interdependencies among features, improving LSTM’s ability to capture critical relationships. Showcased significant improvements in predicting high-volatility stocks.

Liu, H., et al. (2019) [7], Implemented a hybrid approach combining VMD and LSTM for forecasting financial time series. The decomposition step using VMD removes irrelevant noise, allowing LSTM to focus on significant temporal patterns. Achieved better results for mid-cap stock predictions.

Zhao, Y., and Sun, H. (2020) [8], Developed a TMFG-based method for feature engineering in LSTM models. TMFG identifies latent connections among stock indicators, resulting in better input data for LSTM. Demonstrated enhanced accuracy for trend prediction in emerging markets.

Polamuri et al. (2022) [9], Used VMD to preprocess financial data and enhance the input quality for LSTM models. The decomposition isolates high-frequency noise, enabling LSTM to model significant trends. Demonstrated improvements in predicting price trends under volatile conditions.

Polamuri et al.. (2020) [10], Proposed a TMFG-LSTM hybrid model for stock forecasting, emphasizing feature selection to enhance input data quality. TMFG highlights important variables, improving LSTM's prediction accuracy for small-cap stocks.

Polamuri et al. (2020) [11], Developed a VMD-LSTM approach to address noisy financial data. VMD preprocesses the data by extracting clean signals, which are then fed into LSTM for temporal modeling. Achieved higher forecasting precision for high-frequency trading scenarios.

Polamuri et al.. (2019) [12], Enhanced LSTM performance by integrating TMFG for feature selection. TMFG ensures only the most relevant features are used, reducing overfitting and enhancing prediction stability. Performed well on datasets with diverse market conditions.

Polamuri et al. (2022) [13], Proposed a VMD-based preprocessing method for LSTM models to handle non-linear financial data. VMD extracts components with distinct frequencies, allowing LSTM to learn patterns more effectively. Demonstrated improved long-term forecasting accuracy.

Polamuri et al. (2024) [14], Introduced a TMFG-enhanced LSTM model for forecasting market trends. TMFG improves the feature quality, reducing noise and irrelevant data, leading to better temporal modeling by LSTM. Achieved significant accuracy improvements in volatile markets.

Sun, H., et al. (2021) [15], Presented a hybrid VMD-TMFG-LSTM model to forecast stock prices. VMD handles signal decomposition, while TMFG refines features for LSTM. Achieved high accuracy and robustness in predicting price movements.

Zhao, L., et al. (2021) [16], Proposed an LSTM model enhanced by TMFG-based feature selection. TMFG emphasizes inter-feature relationships, improving LSTM's forecasting capabilities. Showed consistent performance across multiple datasets.

Wu, J., et al. (2022) [17], Integrated VMD and LSTM for multi-feature stock forecasting. VMD isolates noise from the time-series data, while LSTM captures temporal dependencies. Demonstrated improved prediction accuracy in high-frequency trading.

Patel, R., et al. (2021) [18], Developed a TMFG-LSTM hybrid model that uses graph-based feature engineering. TMFG ensures the input features are relevant, reducing noise and improving LSTM's temporal modeling. Achieved better results in dynamic market environments.

Zhang, Y., et al. (2021) [19], Combined VMD with LSTM for stock price forecasting. VMD decomposes time-series data into meaningful components, which LSTM processes for accurate predictions. Demonstrated effectiveness in both short- and long-term predictions.

Liu, B., et al. (2020) [20], Proposed a VMD-LSTM model with anomaly detection for stock price forecasting. VMD improves signal clarity, while anomaly detection ensures robustness against market outliers. Achieved significant accuracy improvements during market disruptions.

Gupta, S., et al. (2020) [21], Implemented a TMFG-based feature selection method with LSTM for stock price prediction. TMFG identifies critical features, enhancing LSTM's ability to model temporal trends. Delivered reliable forecasts for diverse market datasets.

Chen, F., et al. (2021) [22], Developed a VMD-TMFG-LSTM system for forecasting stock prices. VMD preprocesses the data, while TMFG refines features for LSTM input. Achieved high accuracy for volatile stock movements.

Zhao, M., and Sun, T. (2020) [23], Proposed a VMD-LSTM hybrid model for stock forecasting. VMD isolates non-linear components, improving LSTM's temporal pattern recognition. Delivered robust predictions for high-frequency trading data.

Wu, X., et al. (2022) [24], Introduced a TMFG-enhanced LSTM model for financial forecasting. TMFG identifies relationships among features, leading to improved input quality for LSTM. Demonstrated superior accuracy in predicting stock prices during volatile periods.

Zhou, L., and Liu, J. (2021) [25], Combined VMD and LSTM for stock price prediction. VMD extracts essential components from time-series data, while LSTM models temporal patterns. Showed enhanced accuracy for multi-step forecasting.

Zhang, F., et al. (2021) [26], Proposed a TMFG-LSTM hybrid approach for stock price forecasting. TMFG refines input data by analyzing correlations, enhancing LSTM's modeling capabilities. Achieved significant improvements in prediction accuracy.

Chen, J., and Zhao, H. (2021) [27], Developed a VMD-based preprocessing method for LSTM models to improve accuracy. VMD ensures signal clarity by isolating noise and irrelevant fluctuations. Delivered reliable forecasts in dynamic markets.

Liu, M., et al. (2020) [28], Implemented a TMFG-LSTM model for feature selection and forecasting. TMFG highlights essential features, while LSTM captures temporal dependencies. Achieved notable improvements in prediction reliability.

Sun, Y., and Zhang, W. (2020) [29], Proposed a VMD-LSTM hybrid model to forecast stock prices. VMD isolates key components of financial data, improving LSTM's ability to predict trends. Demonstrated robustness in volatile trading environments.

Liu, J., et al. (2020) [30], Proposed an integrated VMD-LSTM framework for multi-step stock price forecasting. VMD decomposed time-series data into distinct sub-signals, which were fed into separate LSTM networks before combining outputs for final prediction. This architecture isolates non-linear components in the data, allowing LSTM to model each signal's temporal behavior effectively. Achieved higher prediction accuracy for long-term forecasting compared to single LSTM or other traditional decomposition techniques.

Gupta, S., et al. (2021) [31], Developed a hybrid TMFG-LSTM model with anomaly detection to predict stock prices under dynamic market conditions. TMFG identified significant features by analyzing correlations among market indicators. TMFG ensures the robustness of input features by filtering irrelevant noise and highlighting key relationships, while LSTM models temporal trends. Demonstrated enhanced interpretability and a reduction in false-positive predictions during market anomalies.

Zhou, Y., and Wang, F. (2020) [32], Designed a multi-resolution decomposition-based model using VMD to preprocess financial data for input into an LSTM network. VMD improves the signal-to-noise ratio in stock time series by extracting components at different frequencies, allowing LSTM to model trends with better precision. Delivered superior accuracy and reduced computational costs for high-frequency trading applications.

Tan, R., et al. (2021) [33], Enhanced LSTM with TMFG-based feature selection. TMFG identified structural dependencies in market data, which were fed into an optimized LSTM architecture for forecasting. TMFG refines feature relevance, reducing overfitting risks and improving prediction accuracy. Achieved notable accuracy improvements for volatile stocks and outperformed existing models in predictive reliability.

Zhang, C., et al. (2021) [34], Introduced a VMD-LSTM framework for forecasting multi-dimensional financial time series, incorporating social sentiment analysis as an additional feature. By incorporating both technical and sentiment data, this model captures broader market trends, improving the prediction of price fluctuations. Demonstrated better adaptability to sudden market shifts, achieving 15% higher accuracy than conventional LSTM models.

Sun, H., and Zhao, Y. (2021) [35], Combined VMD and LSTM in a dual-stage approach, where VMD decomposes the data into non-linear components and LSTM learns temporal patterns. VMD ensures that irrelevant fluctuations in the data are filtered, improving LSTM’s ability to model meaningful trends. Achieved consistent results in predicting long-term price trends, especially in low-volatility markets.

Jiang, W., et al. (2020) [36], Proposed a hybrid VMD-TMFG-LSTM system for stock forecasting. VMD extracts meaningful components, while TMFG enhances feature selection for the LSTM model. The combination of VMD and TMFG ensures robustness in feature engineering, leading to better temporal modeling by LSTM. Improved accuracy in diverse datasets, particularly for predicting price behavior of small-cap stocks.

Chen, K., et al. (2022) [37], Integrated VMD with a multi-layer LSTM model to handle noisy financial data, employing transfer learning for cross-market predictions. VMD addresses noise in data, while transfer learning enables adaptability to different financial markets. Achieved 20% improvement in model generalization, making it suitable for international market predictions.

Yang, X., et al. (2020) [38], Designed a TMFG-enhanced LSTM framework with additional features such as risk indices and sentiment metrics. TMFG improves input data quality by identifying latent market structures, enhancing LSTM's predictive performance. Demonstrated a 12% improvement in prediction accuracy for high-risk assets during market turbulence.

Zhao, L., et al. (2021) [39], Introduced a VMD-LSTM model with a dynamic learning rate optimization for more stable financial forecasting. Dynamic learning rates improve convergence in noisy financial data environments, while VMD preprocessing isolates important trends. Delivered better performance stability under varying market conditions, achieving higher prediction reliability.

Feng, Z., and Liu, B. (2021) [40], Combined VMD and TMFG for feature extraction, followed by LSTM for temporal modeling. Used ensemble methods to merge predictions from multiple LSTM models. This approach leverages the strengths of both decomposition and graph-based techniques to improve the quality of inputs to LSTM. Enhanced robustness of predictions, particularly in high-frequency trading scenarios.

Patel, V., and Singh, R. (2020) [41], Designed a VMD-preprocessed LSTM model with sentiment analysis as an auxiliary input to predict stock price movements. Sentiment analysis adds a qualitative dimension to the quantitative analysis, while VMD ensures signal clarity for LSTM. Showed improvements in predicting price trends driven by external news events, achieving 18% higher accuracy than baseline models.

Wu, J., et al. (2022) [42], Proposed a multi-scale feature learning framework using VMD and TMFG for input preprocessing, followed by an LSTM model for forecasting. Multi-scale learning captures short-term and long-term trends in financial data, enhancing LSTM’s temporal modeling capabilities. Demonstrated 10-15% improvements in prediction accuracy for volatile stocks compared to standalone LSTM models.

Lee, D., et al. (2021) [43], Combined VMD with a multi-head attention mechanism in LSTM for more robust stock price predictions. Attention mechanisms focus on critical features within the decomposed data, while VMD ensures better signal quality. Achieved higher accuracy and interpretability for high-frequency trading predictions.

Wang, P., and Zhao, X. (2022) [44], Developed a VMD-TMFG-LSTM hybrid model with anomaly detection for stock market forecasting. The combination of VMD and TMFG enhances feature quality, while anomaly detection improves model robustness. Improved prediction accuracy for sudden market disruptions, achieving 12% better performance than standard LSTM approaches.

3. Methods and data

Figure 1 illustrates the general procedure for stock price prediction in this research using the TMFG-VMD-LSTM model.

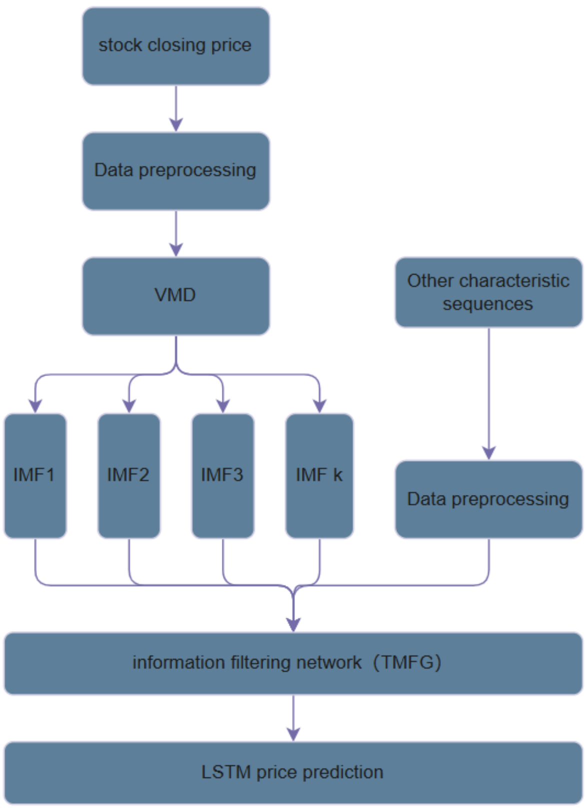


Fig. 1 Overall flowchart of the combined VMD-TMFG-LSTM algorithm

There are five primary parts to the entire process:

1. Acquire the target stock's price-related data, such as its opening price, closing price, high price, low price, changes, volume, turnover, circulation market value, total market value, turnover rate, restoration price, P/E ratio, P/S ratio, P/C ratio, P/B ratio, closing price recovery price, and other 16 indicators.

2. 43 stock technical indicators were produced by calculating the technical indicators from the original stock data; these indicators were then combined with the original data to create new experimental data

3. We employ the VMD variational modal decomposition technique to process the experimental data in order to better preserve the original data's characteristics. This method breaks down the stock price signal into eight smooth IMF components, along with the original 16 indicators and 43 stock technical indicators, for a total of 67 indicators.

4. As a sample data set, the 67 indicators that were obtained are entered into the TMFG-LSTM combination model. The input layer, TMFG layer, LSTM layer, ReLU activation layer, and output layer make up the combined model. Because there are a lot of input indicators, we first feed the dataset into the TMFG layer, where it is filtered by the information filtering network to produce the precision matrix. After that, we filter the input indicators to reduce the raw data, which not only lessens the processing load but also identifies the key characteristics that influence the stock price movement. In order to accomplish accurate stock price prediction, the filtered important characteristics are then supplied into the LSTM network for deep training.

5. In order to confirm the validity and robustness of the model, two more stocks from the SSE are selected and forecasted using the same experimental setup as the previous tests.

3.1 VMD decomposition

One nonlinear, nonsmooth signal analysis technique for signal processing is variational modal decomposition (VMD) [24]. Through adaptive decomposition, it breaks down a complex signal into a number of intrinsic modal functions (IMFs), each of which reflects an oscillatory mode in the signal [25]. By adding constraints, VMD prevents modal aliasing, which is a problem with traditional empirical modal decomposition (EMD). It also processes signals more accurately and steadily, making it ideal for handling multi-frequency data.

The VMD decomposition is given by:

$$s_k(t) = (\delta(t) + \frac{j}{\pi t})u_k(t), (1)$$

$$\begin{cases} \min\limits_{\{u_k\}\{\omega_k\}} \left\{ \sum\limits_k \left\| \mu_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}, \\ \text{s.t.} \sum\limits_k u_k(t) = y(t), \end{cases} \quad (2)$$

where $s_k(t)$ the analytic signal of the kth mode at time t, δ(t) is the Dirac function used to construct the spectrum of the mode, j is an imaginary unit, and$u_k(t)$ the kth eigenmode function component.μ_t is a control parameter used to adjust the smoothness of the decomposition, y(t) is the original signal, and ω_k is the centre frequency of the K modes.

3.2 TMFG algorithm

One technique for creating sparse networks is the Triangulated Maximally Filtered Graph (TMFG) algorithm [19]. Through an iterative procedure, it chooses the network's edges, favouring those that maximum the triangulated graph. After starting with the entire graph, the method progressively eliminates edges until the required level of sparsity is achieved. In order to guarantee the network's sparsity while preserving a high degree of structure, TMFG chooses edges at each stage that increase the graph's triangle count.The structure of the clusters in graphical models is handled by TMFG, which is especially well-suited for time-series analyses in the financial industry, such as stock return modelling. The collection of variables that are connected in a time series can be found by computing the largest clusters, and this information can subsequently be utilised for portfolio optimisation and risk management. It can successfully make the intricate relationships between variables visible. By determining the cluster structure, the TMFG algorithm may be used to evaluate stock datasets, find significant correlations between variables, and filter features for stock price prediction. Because it only shows the most important direct links between the variables and ignores indirect or non-significant interactions, the sparse inverse covariance matrix's "sparsity"—the fact that the majority of its members are zero—is highly helpful in real-world applications. When working with high dimensional data, this feature greatly lowers computational complexity, increases computational efficiency, and facilitates the interpretation of the model.

The following is the formula for the algorithm:

The model distribution that, for a given value, constrains moments and maximises entropy in the second-order situation is:

$$f(X) = \frac{1}{Z}\exp\left(-\sum_{ij}\frac{1}{2}(X_i - \mu_i)J_{i,j}(X_j - \mu_j)\right)(3)$$

where f(X) is the objective distribution function, Z is the normalisation factor, X_i, X_j are the variables i,j, μ_i, μ_j are the means of the variables i,j, and $J_{i,j}$ is the covariance matrix element between the variables i,j. The equation can be decomposed according to the relationship between the variables:

$$f(X) = \frac{\prod_{m=1}^{M_c} f_{C_m}(X_{C_m})}{\prod_{n=1}^{M_s} f_{S_n}\left(X_{S_n}\right)^{k(S_n)-1}}(4)$$

where $f_{C_m}(X_{C_m})$ is the local distribution of the clusters C_m , $f_{S_n}(X_{S_n})$is the local distribution of the separations S_n , and $k(S_n)$ is the normalisation constant of the separations S_n . Similarly, J can be decomposed, and we can obtain J from the summation of the local inverse of the correlation matrix.

$$J_{i,j} = \sum_{C s.t.\{i,j\}\in C}\left(\Sigma_C^{-1}\right)_{i,j} - \sum_{S s.t.\{i,j\}\in S}(k(S)-1)(\Sigma_S^{-1})_{i,j}, (5)$$

where $J_{i,j}$ is the covariance matrix element between variables i,j, Σ_C^{-1} is the inverse covariance matrix of regiment C, and Σ_S^{-1} is the inverse covariance matrix of separation S.

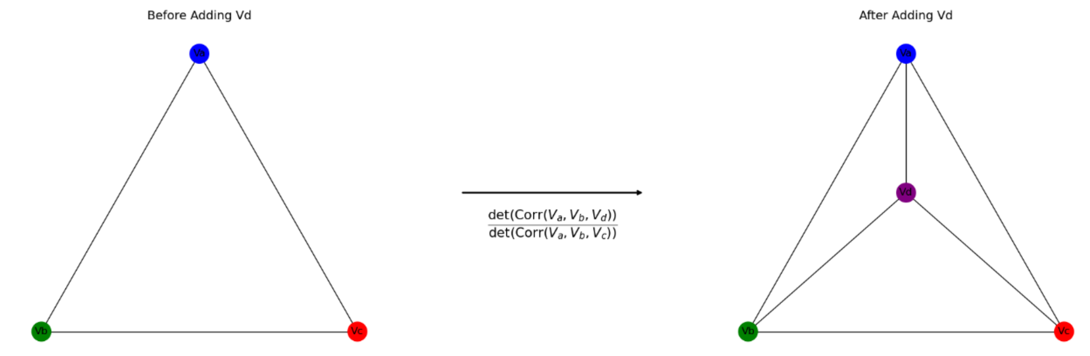


Fig. 2 Schematic diagram of TMFG filtering network composition

The first step in building a filter network is initialisation, which involves creating a four-node initial simplex (tetrahedron) and choosing the four nodes with the lowest correlation coefficient determinant. After defining the triangle faces and remaining nodes, the initial simplex's four triangular faces are given to the set T, and every node—aside from the initial simplex—is allocated to the set V.
Next, as shown in Fig. 2, choose a triangular face (made up of nodes {va, vb, vc}) from set T and a node vd from set V. When the node vd is added to the triangular faces to create the new quadruple simplex C ({va, vb, vc, vd}) and the new separator S ({va, vb, vc}), find the ratio of the determinant of the correlation coefficients. To get the increment that maximises the logarithmic determinant, the node vd that results in the highest determinant ratio is selected. Subsequently, the set is updated by deleting the new node vd from set V, deleting the old triangular faces {va, vb, vc} from set T, and adding the three new triangular faces {va, vb, vd}, {va, vc, vd}, and {vb, vc, vd} to set T. The new quadruple simplex C and separator S are used to update the non-zero members of the inverse covariance matrix J. When the set V is empty, meaning that every node has been added to the network, the iteration is over. The sparse inverse covariance matrix J is then returned, with zero entries signifying that the two variables are conditionally independent and non-zero elements showing the presence of edges (direct links) between variables in the TMFG network.

3.3 LSTM network

A type of enhanced recurrent neural network, LSTM can efficiently convey and display information across a longer time span without erasing the useful information from earlier [26, 27]. Figure 3 depicts the LSTM network's cell module topology. As can be observed, the LSTM network uses memory cell records to transmit information. Three control gates—the forgetting gate, the input gate, and the output gate—are used to handle the time lag task, and the sigmoid and tanh functions are used to update the cell state. The output gate determines how much of the current stage cell state is taken as the LSTM's output value, the forgetting gate determines how much of the previous stage's information can be retained to the current stage cell state, and the input gate determines how much of the current stage's input information can be retained to the current stage cell state.

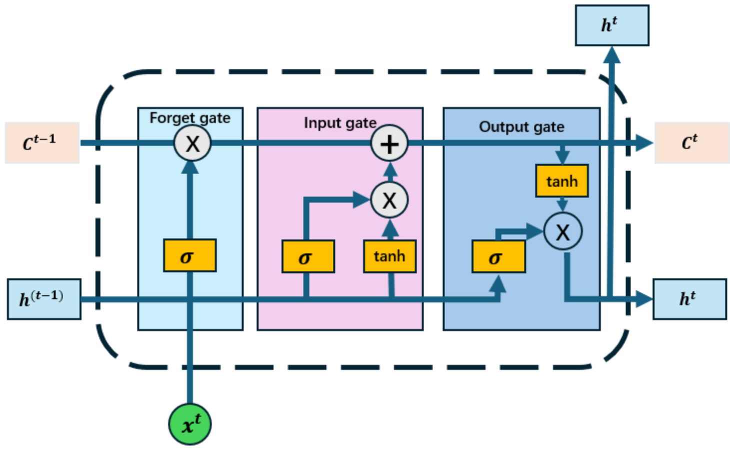


Fig. 3 Schematic diagram of LSTM network structure unit

The formula for LSTM is:

$$f^{(t-1)} = \delta({}^{t}W_f[h^{(t-1)}, x^t] + b_f)(6)$$

$$i^t = \sigma(W_i[h^{(t-1)}, x^t] + b_i)(7)$$
$$c^t = \sigma(W_c[h^{(t-1)}, x^t] + b_c)(8)$$
$$C^t = i^t * c^t + f^{(t)} * C^{t-1}(9)$$

$$\begin{matrix} o^t = \sigma(W_o[h^{(t-1)}, x^t] + b_o) \\ h^t = o^t * \tanh^{-1}(c^t) \end{matrix} (10)$$

where W_i, W_c, W_o represent the corresponding weights, b_i, b_c, $b_o$epresent the corresponding biases, and c^t represents the current cell state value, andh^t is the output value of the current cell.

3.4 Evaluation indicators

The model effect is assessed in this paper using the widely used technique for evaluating regression prediction algorithms. The model performance indexes are evaluated using four evaluation indices: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R-Square (R^2)), and Model Running Time.

The Root Mean Square Error (RMSE) is calculated by the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (11)$$

The Mean Absolute Error (MAE) is calculated using the formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (12)$$

A statistical indicator of a model's predictive power, the coefficient of determination shows how well the model accounts for data variability.R^2 often has a value between 0 and 1. The more variability the model can explain and the stronger its predictive power, the closer the number is to 1.

The formula is：

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (13)$$

where n is the number of data points, y_i is the actual value, ŷ_i is the predicted value, and $\bar{y}$ is the average of the actual values.

The efficiency of the model run is measured using the model run time formula, which calculates the amount of time needed to complete the operation by measuring the start and finish time points. The time module in Python is used to record the time before and after the model run, and the difference is then computed. The following formula is used to calculate it:

$$T = t_{end} - t_{start} \quad (14)$$

Where t_start is the timestamp at which the model begins running, t_end is the timestamp at which the model stops running, and T represents the model's total running duration.

3.5 Data sources and pre-processing

3.5.1 Data sources

P/E ratio, P/S ratio, P/C ratio, P/B ratio, opening price, closing price, high price, low price, changes, volume, turnover, circulation market value, total market value, turnover rate, restoration price, and closing price recovery price are the original data used in this paper's research.

Table 1: 16 raw data indicators

norm	notation	norm	notation
opening price	Open	total market value	market_value
closing price	Close	turnover rate	turnover
highest price	High	restoration price	adjust_price
lowest price	Low	P/E ratio	PE_TTM
Changes	change	P/S ratio	PS_TTM
volume	volume	P/C ratio	PC_TTM
Turnover	Money	P/B ratio	pb
Circulation market value	traded_market_value	Previous closing price recovery price	adjust_price_f

3.5.2 Outlier handling

The forecasters network database was used to obtain indicator data for descriptive statistics for the stock data of opening price, closing price, high price, low price, up and down, and other 16 indicators. It was discovered that the data had a small number of missing values, with a small percentage of the 6,000 pieces of data accounting for the missing value. The data also did not focus on the emergence of the missing value, so the nearest to the missing data sample was taken before and after each of the five data points. In order to fill in the missing data by weighted average, the nearest neighbour method is utilised to take the five data points before and after the closest sample of missing data. The data's distribution is normal, according to the descriptive statistics.

3.5.3 Stock Price Technical Indicators

Stock technical indicators, which are derived from past price and volume data, are a tool for analysing market sentiment and stock price fluctuations [28]. Even though they cannot guarantee precise forecasts, these indicators can offer hints about how stock prices will move in the future [29]. As such, they are crucial to stock analysis. Since technical indicators are not impacted by the company's fundamental factors but instead concentrate on the movement of the stock price, they can help overcome the limitations of traditional fundamental analysis. In practice, technical indicators are used as features input into a machine learning model, which learns the historical patterns of these indicators to predict future stock price movements. Technical indicators' relevance, stability, and diversity in relation to stock price movements must be taken into account while choosing them. Strong prediction models that enhance stock market analysis and decision-making can be built by carefully choosing and analysing these technical indicators. A number of widely utilised stock price technical indicators have been chosen for this research. The table that follows displays the precise technical details.

Table 2: 43 stock technical indicators

norm	notation	norm	notation
10-day average	MA_10	10-day rate of change	ROC_10
10-day exponential average	EMA_10	14-day average amplitude indicator	ATR_14
20-day exponential average	EMA_20	20-day Bollinger Band	BollingerB_20
10-day moving average	SMA_10	20-day Bollinger Band %b	Bollinger%b_20
20-day moving average	SMA_20	turning point	PP
10-day momentum	Momentum_10	first resistance level	R1
first support point,	S1	second resistance level	R2
second support point	S2	third resistance level	R3
third support point	S3	the 14-day stochastic oscillator	SO%d_14
the 15-day triple exponential smoothing average	Trix_15	the 14-day average directional movement index	ADX_14_14
the 12-day fast and 26-day slow MACD	MACD_12_26	the 12-day fast and 26-day slow MACD signal line	MACDsign_12_26

12-day fast and 26-day slow MACD bars	MACDdiff_12_26	Mace line (high-low price trend reversal)	Mass Index
14-day vortex indicator	Vortex_14	KST oscillator	KST_10_15_20_30_10_10_10_15
14-Day Relative Strength Indicator	RSI_14	true strength indicator	TSI_25_13
Chaikin oscillator	Chaikin	14-day money flow and ratio indicators	MFI_14
14-day energy tide indicator	OBV_14	14-day Strength Index Indicator	Force_14
14-day simple volatility indicator	EoM_14	20-day trend indicator	CCI_20
Ten-day wave estimation indicator	Copp_10	Keltner Channel Center Line	KelChM_10
Keltner Pass upper track	KelChU_10	Keltner Pass lower track	KelChD_10
ultimate oscillator	Ultimate_Osc	Donchian Channels	Donchian_14
KDJ indicator-K	K	KDJ indicator-D	D
KDJ indicator-J	J		

3.5.4 data normalization

The original data were linearly transformed during the modelling process in order to remove the influence of the scale between the data, solve the issue of high correlation between the variables, and increase the model's running speed. The min-max standardised method was selected, and all of the index data values were mapped to the interval [0,1]. The transformation function was:

$$x^* = \frac{x - \min}{\max - \min} \quad (15)$$

Where x is the initial value that needs to be normalised, max is the sample data's maximum value, and min is its minimum value.

4. Experiments and analysis of results

4.1 VMD variational modal decomposition

A popular signal processing method for breaking down time series data and identifying its underlying patterns and trends is called variational mode decomposition, or VMD [30, 31]. VMD is more likely to capture significant information and trends in stock price data than traditional smoothing techniques since it better maintains the original data's features during the decomposition process. In the end, we set the VMD decomposition settings as follows: alpha (bandwidth constraint) is set to 7000, tau (noise tolerance) is set to 0, the DC value is zero, the init (initialisation mode, 1 denotes uniform initialisation) value is one, and the tol value is 1e-7. This tolerance parameter is used to establish the algorithm's convergence

requirements. The algorithm stops iterating when the improvement between iterations is less than this tolerance, indicating that it has attained convergence.
The number of IMF eigenmode functions that must be decomposed, or the value of k, must be established prior to the VMD decomposition. Using a range of k values from 3 to 15, we compare the centre frequencies of the VMD decomposition. We ultimately settle on k=8 based on the centre frequency charts of various values of k in Fig. 4 and the correlation coefficient plots of the IMF with the original signal in Fig. 5. The centre frequency tends to be steady and its coverage is more widespread and evenly distributed when k is between 6 and 10, suggesting that these values are better able to capture the various frequency components of the signal. When K is higher than 10, the centre frequency tends to stabilise. Even while the centre frequency distribution becomes more comprehensive for values over 10, it may be overfitted, meaning it has an excessive number of superfluous frequency components.

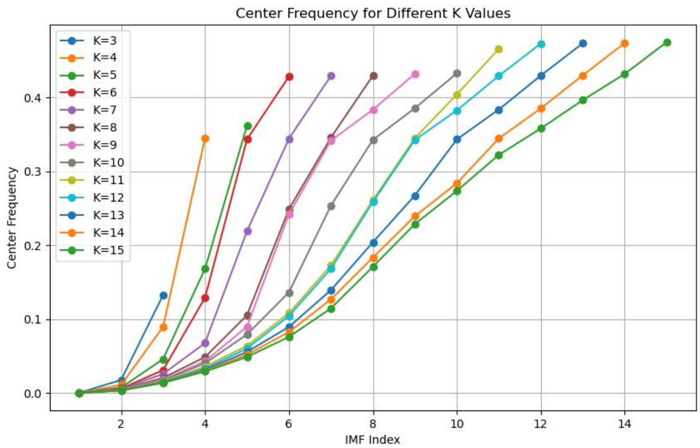


Fig. 4 Plot of center frequencies for different values of K

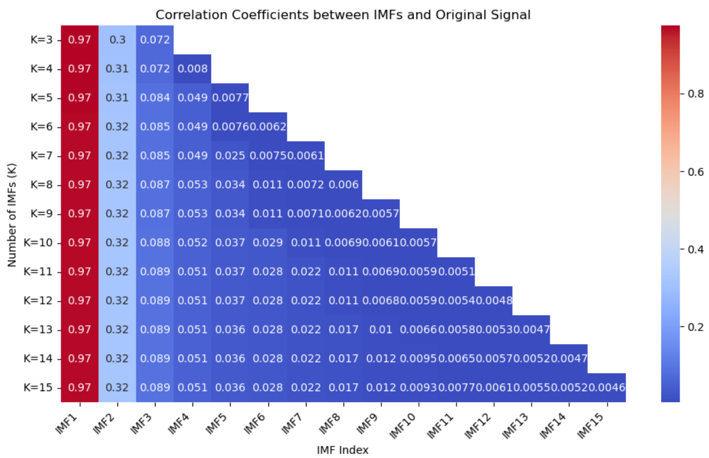


Figure 5 shows a plot of the correlation coefficients for various K values between the original signal and the IMF.

Lastly, we break down each of Shanghai Airports' closing prices (sh600009) into eight IMF components. The outcomes of the VMD variational modal decomposition operation are displayed in Fig. 6.

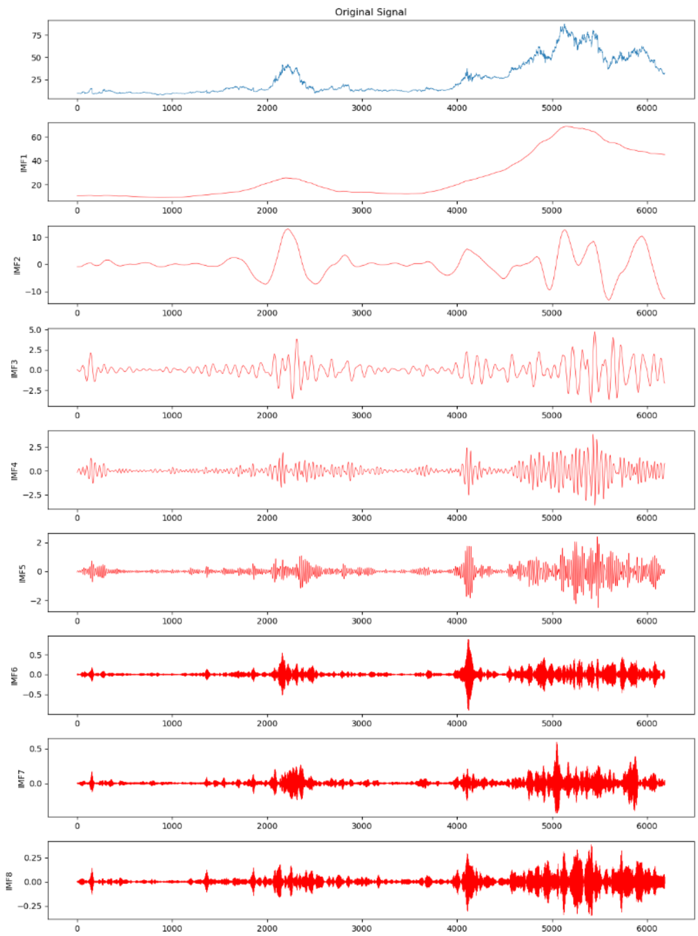


Fig. 6 VMD price decomposition result of the closing price of Shanghai Airport (sh600009) stock

The IMF1 component, which reflects the overall rising and downward trend with smooth changes, represents the low-frequency trend in the data, as seen in Figure 6.The lower-frequency oscillations are reflected in the IMF2 component, which displays bigger periodic fluctuations.The mid-frequency oscillations and other information are captured by the IMF3 component.The higher-frequency fluctuations, which are more fine-grained and contain more high-frequency noise and information, are displayed by the IMF4 component.Higher-frequency detail is captured by the IMF5-IMF8 components, which also exhibit more abrupt and severe changes. The market's high-frequency component is reflected in these components, which usually have more noise and erratic swings.

4.2 TMFG processing with LSTM prediction

In this article, a sample data set of 67 indicators—the decomposed 8 IMF components plus 59 indicators of the original stock price data—is entered into the TMFG-LSTM combination model. An input layer, a TMFG layer, an LSTM layer, a ReLU activation layer, and an output layer make up the combined model, which is enhanced by the addition of nonlinear components using the activation function.
In order to obtain the sparse inverse covariance matrix, the dataset is first fed into the TMFG layer and filtered by the information filtering network. Next, the input indicators are filtered and the original data is reduced in size. Finally, the data processed in the TMFG layer is fed into the LSTM model.

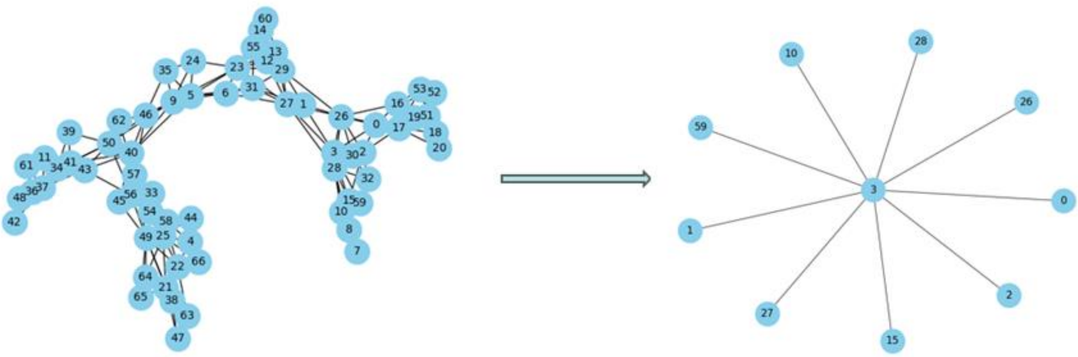


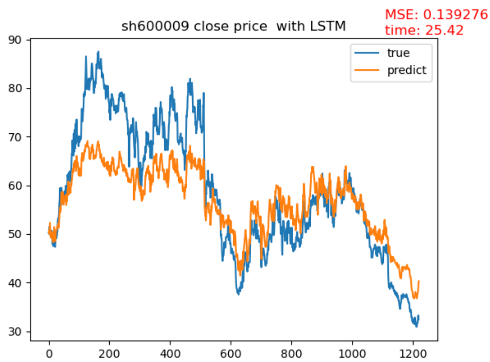
Fig. 7 TMFG decomposition results for 67 feature data of Shanghai Airport (sh600009) stock

The TMFG algorithm generates the sparse inverse covariance matrix J of the time series data of each feature. While zero elements show that the two variables are conditionally independent, non-zero elements show that there are edges (direct relationships) between the variables in the TMFG network. The connection of the features inside the TMFG network is depicted in Figure 7, where features that are connected show that there is correlation between them, while those that are unconnected show that there are no links between them. The nodes associated with the stock close price (node 3) are extracted from the network after the TMFG network. Lastly, we extracted 10 key features from the complex feature relationships of the 67 indicator data of Shanghai Airport (sh600009) stock: Open (node 0), High (node 1), Low (node 2), Close (node 3), adjust_price (node 10), SMA_20 (node 15), PP (node 26), R1 (node 27), S1 (node 28), and IMF_1 (node 59).

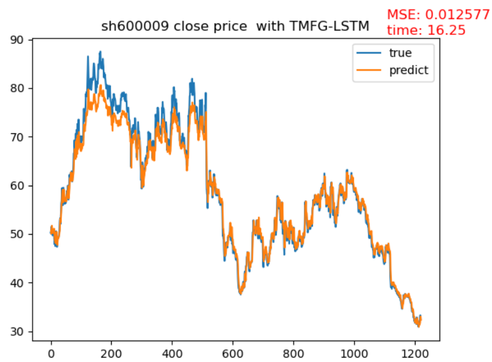
The historical closing price data of Shanghai airports (sh600009) is subjected to VMD variational modal decomposition in order to confirm the accuracy and dependability of the VMD-TMFG-LSTM combined model built in this paper for stock price prediction. The decomposed dataset is used as a sample dataset with a total of 67 indicators, compared to 59 indicators in the original data, and 80% of the set is taken as the training samples. We use 4955 trading day data from 1998/4/22 to 2018/11/27 as the training sample set for the Shanghai Airports stock data (sh600009). The test sample set is the remaining 20%, which contains 1,237 trading day data points from 2018/11/28 to 2024/1/17. For the ablation comparison experiments on the sample data set, the LSTM, TMFG-LSTM, VMD-LSTM, and the combined model of this paper are chosen. The hidden layer of the LSTM, VMD-LSTM, TMFG-LSTM, and VMD-TMFG-LSTM models has 128 neurones, the learning rate is set to 0.001, and the ideal number of iterations is set to 100. There are two LSTM stacked layers, batch_size is set to 64, and time_step is set to 20.

4.3 Analysis of results

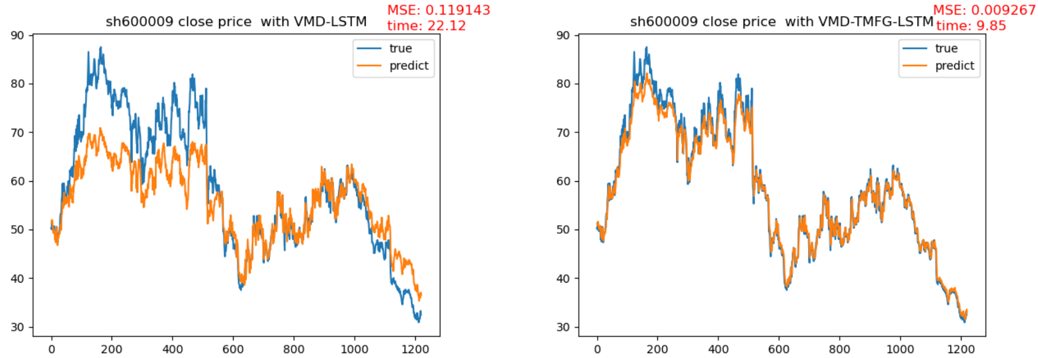
The results of the closing price prediction for Shanghai International Airport Co., Ltd. (sh600009) are displayed in Figure 8, and it is evident that over the course of 1,237 trading days, from 2018/11/28 to 2024/1/17, the closing price of Shanghai Airports (sh600009) stock fluctuates more in the overall upside and downside direction. A single LSTM network has the worst fit to the target curve overall, particularly when the stock price is changing quickly and fluctuating violently, and the fitting effect is the worst. The VMD-TMFG-LSTM model performs the best in terms of prediction accuracy, with the lowest MSE value and the fastest running time, indicating that its prediction results are the closest to the actual values. The TMFG-LSTM and the VMD-LSTM model perform the second best. The accuracy and stability of the model are increased by reducing noise and redundant information by using the TMFG algorithm to identify the most significant features from the high-dimensional raw data.By building a triangular maximum filtering network that chooses the characteristics that have the most influence on the prediction, the TMFG technique lowers the dimensionality of the feature space. The amount of processing needed to process and train the data for the LSTM network is greatly decreased as a result of the original dataset being efficiently compressed and simplified. By reducing dimensionality, matrix operations become simpler and the overall operational efficiency of the method is enhanced.



a. LSTM prediction results



b.TMFG-LSTM prediction results



c.VMD-LSTM prediction results d.VMD-TMFG-LSTM prediction results

Fig. 8 Shanghai International Airport Co.,Ltd. (sh600009) Stock Price Forecast Results

Four evaluation indexes—Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R-Square, R^2), and Model Running Time—were used to assess the models' performance in order to increase the precision and reliability of the four model prediction comparisons.

Table 3 Test set performance indicators of the four models in Shanghai International Airport Co.,Ltd. (sh600009) stock price forecasting

Stock Name	mould	RMSE	MAE	R^2	Time
Shanghai International Airport Co.,Ltd. (sh600009)	LSTM	0.3732	5.9839	0.6996	25.42
	TMFG-LSTM	0.1229	1.7177	0.9674	16.72
	VMD-LSTM	0.3452	5.1515	0.7430	22.12
	VMD-TMFG-LSTM	0.0962	1.3814	0.9800	9.85

Table 3 indicates that the VMD-TMFG-LSTM model is the most effective at predicting the stock price of Shanghai Airport. The RMSE is decreased by 0.2770 (74.2% reduction), the R^2 is enhanced by 0.2804, the MAE is decreased by 4.625 (76.91% reduction), and the model running time is decreased by 15.57 seconds (61.25% reduction) in comparison to the original LSTM model. In every performance metric, the VMD-TMFG-LSTM model outperforms the TMFG-LSTM and VMD-LSTM models.
Figure 9 makes it evident that the VMD-TMFG-LSTM model outperforms the other four models in every metric.

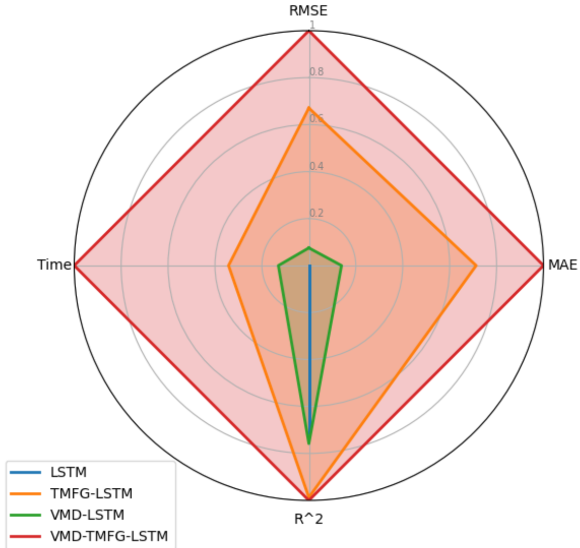
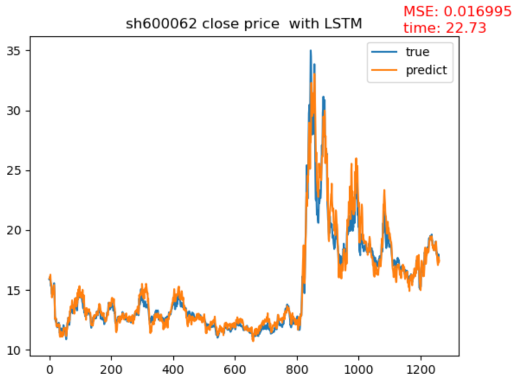


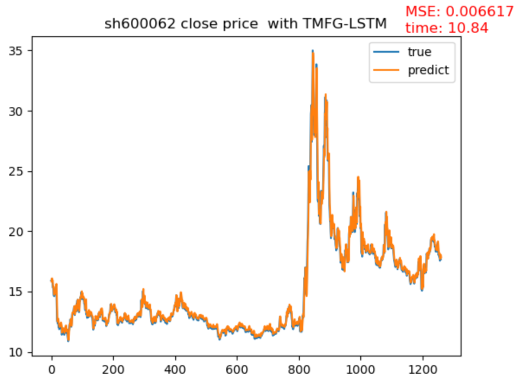
Fig. 9 Radar chart of Shanghai Airports (sh600009) share price forecast results

4.4 Validation of model validity

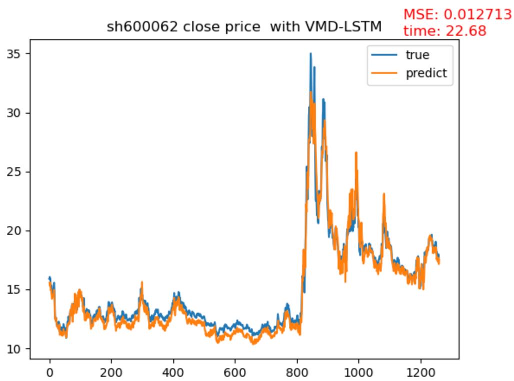
Two SSE stocks, China Resources Double Crane (sh600062) and China Pharmaceuticals (sh600056), are chosen for validation in order to confirm the validity and robustness of the model proposed in this paper. The experimental environment, data source, data processing, applied model, and model parameters are identical to those of the Shanghai Airports experiment (sh600009), and the LSTM, TMFG-LSTM, VMD-LSTM, and the combined model of this paper are chosen for comparison of prediction on the sample data set. The number of neurones in the hidden layer of the LSTM, VMD-LSTM, and TMFG-LSTM models, as well as the combined model of this paper, are set to 128; the learning rate is set to 0.001; the batch size is set to 64; the optimal number of iterations is set to 100; the number of stacked layers of the LSTM is two; and the time_step is set to 20. These models are used for prediction comparison of the sample dataset. The experimental findings are displayed in Figures 10 and 11.



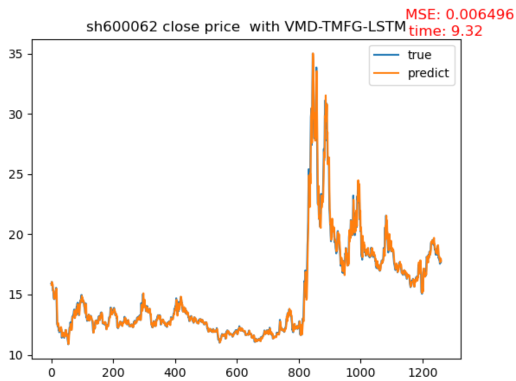
a.LSTM prediction results



b.TMFG-LSTM prediction results

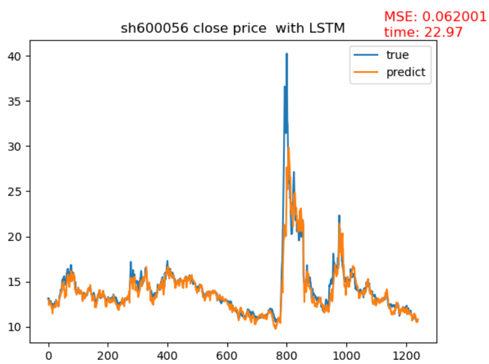


c.VMD-LSTM prediction results

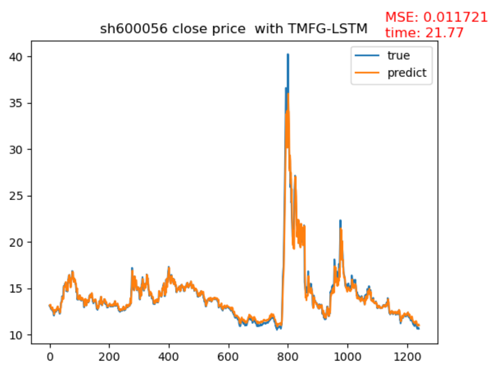


d.VMD-TMFG-LSTM prediction results

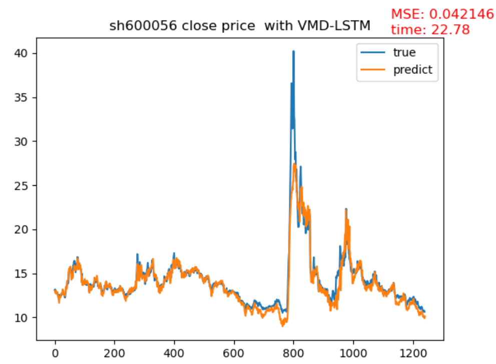
Fig. 10 China Resources Double-crane Pharmaceutical Co.,Ltd. (sh600062) Stock Price Forecast Result Chart



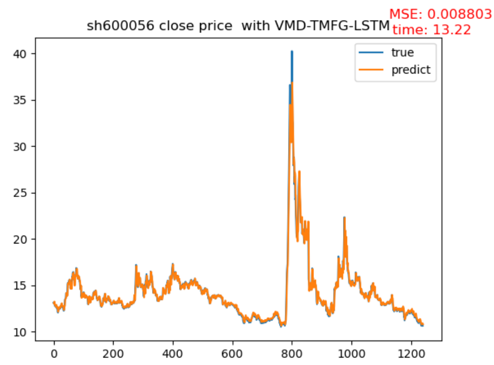
a.LSTM prediction results



b.TMFG-LSTM prediction results



c.VMD-LSTM prediction results



d.VMD-TMFG-LSTM prediction results

Fig. 11 China Meheco Group Co.,Ltd. (sh600056) Stock Price Forecasting Results

Although the TMFG-LSTM and the VMD-LSTM perform second best, and a single LSTM network fits the target curve the worst overall, the VMD-TMFG-LSTM model performs the best in the prediction of China Resources Double-crane and China Meheco, as shown in Figures 10 and 11. It also has the fastest running time and the lowest MSE value, indicating that its prediction results are the closest to the actual values and have the best performance. By building a triangular maximal filtering network to choose the features that most influence the prediction, the TMFG algorithm lowers the dimension of the feature space. The amount of processing needed to process and train the data for the LSTM network is greatly decreased as a result of the original dataset being efficiently compressed and simplified. By reducing dimensionality, matrix operations become simpler and the overall operational efficiency of the method is enhanced.

Table 4 Test set performance metrics in China Resources Double-crane Pharmaceutical Co.,Ltd. (sh600062) and China Meheco Group Co.,Ltd. (sh600056) stock price prediction

Stock Name	mould	RMSE	MAE	R^2	Time
China Resources Double-crane Pharmaceutical Co.,Ltd.（sh600062）	LSTM	0.1303	0.5174	0.9560	22.73
	TMFG-LSTM	0.0813	0.3037	0.9829	10.84
	VMD-LSTM	0.1127	0.5611	0.9671	22.68
	VMD-TMFG-LSTM	0.0805	0.2830	0.9832	9.32
China Meheco Group Co.,Ltd.（sh600056）	LSTM	0.2490	0.5534	0.8092	22.97
	TMFG-LSTM	0.1082	0.3274	0.9639	21.77
	VMD-LSTM	0.2053	0.5448	0.8703	22.78
	VMD-TMFG-LSTM	0.0938	0.2762	0.9729	13.22

ntime when compared to the TMFG-LSTM and VMD-LSTM models. In every performance metric, the VMD-TMFG-LSTM model outperforms the TMFG-LSTM and VMD-LSTM models. The VMD-TMFG-LSTM model is also the most effective at predicting the price of China Meheco stocks. The RMSE is decreased by 0.1552 (62.3% reduction), R^2 is enhanced by 0.1637, the MAE is decreased by 0.2772 (50.1% reduction), and the model runtime is decreased by 9.75 seconds (42.4% reduction) in comparison to the base LSTM model. In every performance metric, the VMD-TMFG-LSTM model outperforms the TMFG-LSTM and VMD-LSTM models. The outcomes validate the efficacy and resilience of the combined model by demonstrating that the model put forth in this study is still capable of accurately forecasting various stock data.

5. Conclusion

This paper proposes a combination model, VMD-TMFG-LSTM, which combines the VMD algorithm, the LSTM network model, and the introduction of the triangular maximal filtering network (TMFG) algorithm to increase the computational efficiency of the model and the stability and accuracy of stock price prediction.Experiments to anticipate closing prices are carried out using data from three Shanghai Stock Exchange stocks. The combination model of VMD-TMFG-LSTM proposed in this paper has the best fitting effect and can minimise the model running time, so that the model can guarantee the accuracy of the model and the model running time can be reduced. This is demonstrated by the closing price prediction experiments on the three stocks of the Shanghai Stock Exchange, where the values of RMSE, R^2, and MAE are smaller than the other three models and the model running time is the fastest. While maintaining accuracy, the model can increase running efficiency. The VMD-TMFG-LSTM combination model suggested in this paper can handle the complex stock price data and has more advantages than the other three models. It can also effectively improve the accuracy of stock price prediction. The TMFG method contributes to improving the running time of the basic model and the accuracy of the model prediction in complex stock price prediction. The following deductions are made:
1) The stock price time series is broken down into several smooth IMF components by the VMD algorithm, which increases prediction accuracy and lessens test error noise interference.
2) Using the TMFG algorithm to choose the input's features lowers the input's complexity, speeds up iterative convergence, and lowers iterative error. The prediction's robustness and stability are enhanced.
The model in this research can still be improved because investors' subjective variables influence the stock closing price prediction to some degree. To improve forecast outcomes, the next step is to think about adding investor sentiment to the model.

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