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Financial Time Series Data Forecasting based on CEEMDAN-BiGRU-BO Model

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Abstract

In the quantitative investment and risk management system, financial data prediction, as a core link, its accuracy directly determines the efficiency of asset pricing and the return level of the investment portfolio. However, under the combined influence of multiple factors such as macroeconomic fluctuations, heterogeneity of investor behavior, and unexpected events, the financial market exhibits significant nonlinearity, non-stationarity, and high noise characteristics, posing severe challenges to traditional prediction models. To address this issue, this paper develops a hybrid model integrating Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Bidirectional Gated Recurrent Unit (BiGRU) and Bayesian Optimization (BO) to boost the forecasting accuracy and resilience of financial time series data. This model first introduces CEEMDAN in the feature engineering stage to adaptively decompose the data, extract the intrinsic mode function (IMF) and residual components, effectively alleviating the non-stationarity and complexity of the data. Subsequently, in the prediction stage, a BiGRU is adopted to enhance the model's capacity to model long-term trends and sequence structures. Finally, BO is utilized to determine the optimal parameter combination under different datasets. Based on the above methods, this paper takes the index of the Shanghai stock exchange (SSEC), the index of the stock exchange of Thailand (SET) and the Korea composite stock price index (KOSPI) as empirical data for verification. The findings demonstrate that the hybrid model achieved mean absolute percentage error (MAPE) indicators of 0.188%, 0.291% and 0.185% respectively, which were significantly lower than those of other control models, verifying its stability and adaptability in the complex financial environment.

Keywords

CEEMDAN; BiGRU; Bayesian Optimization; Time Series Forecasting.

1. Introduction

With the accelerating evolution and growing complexity of global financial markets in recent years, financial time series data has exhibited high volatility and structural diversity. Influenced by multiple factors, including changes in macroeconomic policies, the international political environment, and shifting market expectations, financial market behavior has become increasingly complex, with data exhibiting increasingly pronounced nonlinearity, nonstationarity, and sudden fluctuations. Against this backdrop, extracting valuable information from massive amounts of historical data and improving the predictability of financial data have become critical challenges in quantitative investment and risk management. This not only impacts the scientific and effective nature of asset allocation but also directly influences the stability and returns of investment strategies.

Extensive and in-depth investigations into this topic have been carried out by numerous researchers, and gradually formed three types of forecasting methods with statistical

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econometric models, artificial intelligence models (AIM), and hybrid forecasting models as the core. Commonly used econometric models include the vector autoregression model (VAR), the autoregressive moving average model (ARIMA), and the generalized autoregressive conditional heteroskedasticity model (GARCH) model [1-4]. These models can better capture the trend and cyclical changes in time series by analyzing historical data. Their advantages of simple structure and high computational efficiency also enable them to perform well when processing data with low volatility.

In recent years, machine learning models (MLM) such as random forest (RF), support vector machine (SVM), and extreme gradient boosting (XGBoost), as well as deep learning models (DLM) such as recurrent neural network (RNN) and gated recurrent unit (GRU), have been widely used in many fields due to their powerful data processing capabilities and efficient predictive analysis capabilities [5-11]. Bhupender and Navsal systematically evaluated various prediction models including artificial neural network (ANN), RF, and SVM, and compared the prediction performance of each model based on seven statistical indicators. The results showed that RF was lower than other models in key evaluation indicators such as mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), showing stronger predictive ability [12]. Will drew inspiration from biological neural mechanisms and constructed a time series prediction model based on the RNN model. This model can fully utilize the time dependency in historical data and is suitable for modeling dynamic changes in the stock and financial technology markets. The results of their research show that RNN performs well in forecasting tasks for various investment portfolios, with higher accuracy than the logistic regression (LR) [13]. Lu et al. proposed a new probabilistic load forecasting model that uses a bidirectional gated recurrent unit (BiGRU) to extract implicit features in the data. After fully adjusting the hyperparameters, both the accuracy and generalization capability of the model are strengthened, providing an effective solution for short-term load forecasting [14]. However, this type of method still faces limitations such as low computational efficiency, insufficient model interpretability, and cumbersome parameter tuning when processing large-scale data and complex tasks [15].

In order to break through the above research bottlenecks, more scholars have turned their attention to more sophisticated model structure design and multi-algorithm hybrid prediction framework. By optimizing the model structure, the efficiency of feature extraction is improved, and the advantages of different algorithms are combined to improve the overall accuracy and robustness of the model. As noted by Satya, stock data is characterized by widespread noise and irregularity, the prediction model must integrate appropriate and effective feature engineering components. They used discrete wavelet transform (DWT) to transform the data. Empirical evidence indicates that this approach markedly enhances both the prediction accuracy and the general performance of the model [16]. Wang et al. introduced the Pearson correlation coefficient under the framework of a hybrid DLM, identified and retained features strongly correlated with closing prices for model input, and combined singular spectrum analysis (SSA) to break down the stock price series, thereby reducing data noise and optimizing the model structure [17]. Li et al. combined back propagation neural network (BPNN) with ensemble empirical mode decomposition (EEMD) to construct a novel prediction model. Experimental results indicate that EEMD is effective in mitigating noise present in the data, enhance the robustness of the model, and its overall prediction accuracy is higher than that of the traditional BPNN [18]. Ali et al. used genetic algorithm (GA) and simulated annealing (SA) to optimize the parameters of ANN, thereby enhancing the model’s capacity to generalize to unseen data [19]. Chauhan predicted the Nifty 50 index based on a DLM. In order to highlight the optimization results, particle swarm optimization (PSO) was introduced to optimize the configuration parameters of the model, which increased the accuracy from 56.66% to 57.64%, confirming the role of PSO in enhancing predictive accuracy and stability [20].

ISSN: 2692-7608 DOI: 10.6981/FEM.202512_6(12).0008

Based on the above literature, the existing literature generally has the following shortcomings.

(1) The disconnect between decomposition and prediction. Most studies use fixed decomposition parameters to process different market data, failing to establish a mechanism linking the dynamic characteristics of financial markets with the decomposition parameters.

(2) The problem of a single optimization dimension. Existing research has significant limitations in parameter optimization. Traditional manual parameter tuning relies on subjective experience and is prone to bias. While algorithms such as grid search (GS) and random search (RS) can achieve automated parameter tuning, their traversal parameter space exploration mechanism is computationally expensive and prone to falling into local optimal solutions.

(3) Deficiencies exist in model universality verification and architecture design. Most forecasting models are only validated in a single market and use only hybrid models that have not been thoroughly designed.

Based on this, this paper puts forward a novel model that integrates CEEMDAN, BiGRU, and BO. By leveraging the advantages of these models in feature decomposition, comprehensive prediction, and global optimization, this model improves its predictive accuracy and generalization capabilities. It possesses the following three innovations.

(1) CEEMDAN adaptive decomposition. This study introduces the CEEMDAN method, which exhibits adaptive properties and automatically adjusts key parameters such as noise amplitude and number of integrations during the decomposition process to achieve optimal signal decomposition. Compared to traditional empirical mode decomposition (EMD) methods that require manual parameter setting, CEEMDAN uses an adaptive mechanism to automatically adapt to the dynamic characteristics of different financial market data, effectively improving the stability and accuracy of the decomposition and providing a higher-quality input foundation for subsequent predictions.

(2) Collaborative optimization mechanism. Based on the predictive model, BO is used to globally optimize key hyperparameters, overcoming the limitations of traditional manual parameter tuning, GS, and RS. BO efficiently explores the parameter space by constructing a surrogate model, significantly reducing computational costs while effectively avoiding local optima and improving the model's generalization performance and predictive stability.

(3) BiGRU structural design. To address the asymmetric volatility of financial markets, a BiGRU architecture was designed and applied to achieve bidirectional modeling of historical information, fully capturing the dynamics of both rising and falling markets. Furthermore, the model was systematically validated using data from multiple representative financial markets in Asia, providing strong support for its universal applicability.

2. Model Structure

2.1. CEEMDAN

CEEMDAN is an improved empirical mode decomposition method that overcomes the modal aliasing problem of EMD when decomposing complex signals by introducing adaptive noise. It can more effectively handle nonlinear and non-stationary signals and provide more accurate decomposition results. The decomposition steps are described below.

Step 1: Initialize the raw signal:$r_0(t) = x(t)$.

Step 2: Decompose first-order IMF, namely IMF_1.

(2.1) Adding complementary noise: Add multiple sets of positive and negative noise to $r_0(t)$ to generate noisy signals $r_0^+(t)$ and $r_0^-(t)$, where ε is the noise intensity and $w_i(t)$ denotes the white noise added for the i-th time.

ISSN: 2692-7608 DOI: 10.6981/FEM.202512_6(12).0008

$$r_0^+(t) = r_0(t) + \varepsilon w_i(t) \tag{1}$$

$$r_0^-(t) = r_0(t) - \varepsilon w_i(t) \tag{2}$$

(2.2) Perform EMD on each noisy signal to obtain its own first-order IMF, denoted as $IMF_1^{+,i}(t)$ and $IMF_1^{-,i}(t)$.
(2.3) Calculate IMF_1, where N is the total number of IMF components.

$$IMF_1(t) = \frac{1}{2N}\sum_{i=1}^{N}(IMF_1^{+,i}(t) + IMF_1^{-,i}(t)) \tag{3}$$

(2.4) Subtract the IMF component from the original signal and update the residual.

$$r_1(t) = r_0(t) - IMF_1(t) \tag{4}$$

Step 3: Repeat step 2 for the new residuals.

$$r_2(t) = r_1(t) - IMF_2(t) \tag{5}$$

Step 4: When the residual becomes a monotonic signal, that is, the IMF can no longer be decomposed, the iteration stops.

2.2. BiGRU

GRU is an improved RNN. By incorporating a gating mechanism, it mitigates the issues of gradient vanishing and exploding in traditional RNN, enabling it to better capture dependency information in long sequences. The GRU architecture is centered on two primary gates: the update gate and the reset gate. The update gate determines the extent to which the current hidden state incorporates information from the previous hidden state, while the reset gate determines how the current input is combined with historical information. The GRU state update is defined as:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{6}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{7}$$

$$\hat{h}_t = tanh(W_h x_t + r_t \odot (U_h h_{t-1}) + b_h) \tag{8}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widehat{h_t}) \tag{9}$$

Among them, z_t and r_t correspond to the update and reset gates respectively, $\hat{h}_t$ denotes the candidate hidden state, h_{t-1} refers to the hidden state vector of the current time, $\odot$ represents the element-by-element product, σ refers to the Sigmoid activation function, tanh denotes the hyperbolic tangent function. w, U are the respective weight matrices for the input and hidden state, and b represents the bias vector.

On this basis, GRU further introduces a bidirectional structure to model the forward and reverse information of the sequence respectively, thereby obtaining richer contextual features. Let $\vec{h}_t$ and $\overleftarrow{h}_t$ denote the hidden states of the forward and reverse GRU, the output of the BiGRU

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is expressed by concatenating the hidden states of the two directions. Its network structure is shown in Fig. 1.

$$h_t^{BiGRU} = [\overrightarrow{h}_t; \overleftarrow{h}_t] \tag{10}$$

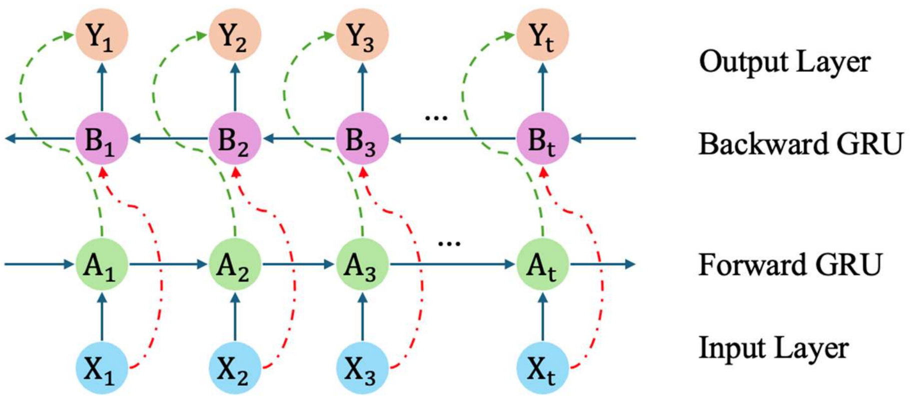

Fig. 1 The structure of one GRU neuron

2.3. BO

Bayesian optimization is an advanced global search technique that is particularly suitable for optimization problems with objective functions that are expensive to evaluate or cannot be explicitly expressed. Its core idea is to maximize the expectation of the objective function at each sampling time through the construction of a probabilistic model for the objective function, which enables rapid convergence toward the global optimum.

The Bayesian optimization process typically begins by constructing an approximate distribution for the objective function. Let $m(x)$ be the mean of the objective function at input x, and $k(\cdot)$ denotes the kernel function that quantifies the correlation between x and x′. The Gaussian process underlying the model is given by:

$$f(x) \sim \varrho\rho(m(x), k(x, x')) \tag{11}$$

In Bayesian optimization, the predicted mean $\mu(x)$ and uncertainty $\sigma(x)$ are updated after each sampling.

$$\mu(x) = K(x, X)[K(X, X) + \sigma_n^2 I]^{-1} y \tag{12}$$

$$\sigma^2(x) = k(x, x) - K(x, X)[K(X, X) + \sigma_n^2 I]^{-1} K(x, X)^T \tag{13}$$

And X represents the observed point, y is the corresponding objective function value,σ_n^2 refers to the noise variance, and I denotes the unit matrix.

The acquisition function guides the selection of the model's next sampling point, balancing the choice between high uncertainty areas and known high mean points. Common acquisition functions are as follows:

(1) Expected Improvement (EI):

$$\pi_{EI}(x) = (f(x^*) - \mu(x))\Phi(Z) + \sigma(x)\phi(Z) \tag{14}$$

ISSN: 2692-7608 DOI: 10.6981/FEM.202512_6(12).0008

$$Z = \frac{f(x^*) - \mu(x)}{\sigma(x)} \tag{15}$$

Here, $f(x^*)$ represents the function value at the current optimal target, $\Phi(Z)$ denotes the cumulative distribution function of the standard normal distribution, and $\phi(Z)$ denotes its probability density function.

(2) Upper Confidence Bound (UCB):

$$\pi_{UCB}(x) = \mu(x) + \kappa \cdot \sigma(x) \tag{16}$$

Here, k is a parameter that adjusts the weight between the mean and uncertainty. In this way, Bayesian optimization strikes a balance between exploring unknown regions and leveraging the current optimal solution, effectively approaching the global optimal solution. Fig. 2 visually illustrates the specific process of Bayesian optimization of BiGRU.

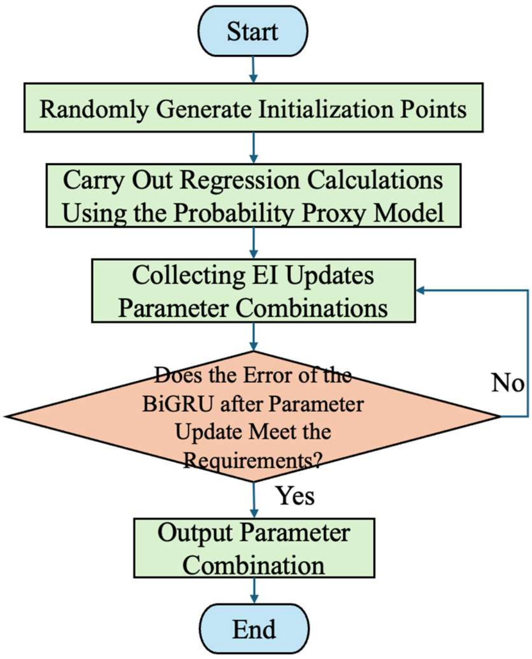

Fig. 2 Bayesian algorithm optimization BiGRU structure diagram

2.4. CEEMDAN-BiGRU-BO

This study introduces a CEEMDAN-BiGRU-BO–based model for stock price prediction. The specific steps are as follows. Fig. 3 shows the hybrid model structure.

(1) The CEEMDAN technique is employed to perform adaptive decomposition of financial stock index data and extract the corresponding intrinsic mode functions (IMF).

(2) The original features collected are integrated with the IMFs to construct a new dataset, after which the dataset is partitioned into training, validation, and test subsets in a 70%:15%:15% ratio.

(3) A BiGRU model is constructed on the training and validation sets, leveraging its bidirectional structure for modeling bidirectional dependencies within the time series, thereby more comprehensively learning the temporal information of the data. Furthermore, a BO method is introduced to dynamically select the optimal hyperparameters of the model, improving the model's generalization ability.

ISSN: 2692-7608 DOI: 10.6981/FEM.202512_6(12).0008

(4) The forecasting accuracy of the hybrid model is evaluated on the test set, and a horizontal and vertical comparative evaluation system is constructed to comprehensively assess the model's merits and drawbacks.

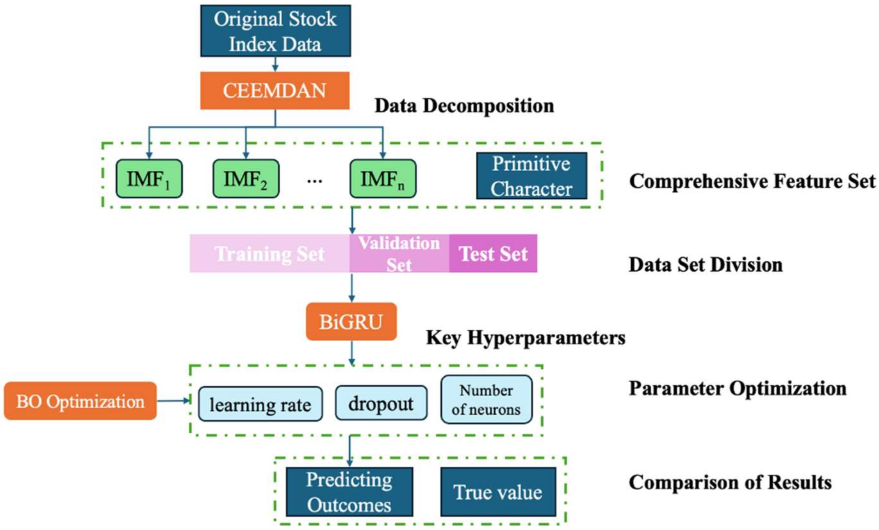

Fig. 3 Hybrid model process

3. Data Processing

3.1. Data Description

This study adopts data from three representative Asian stock indices: China's Shanghai composite index (SSEC), the stock exchange of Thailand index (SET), and South Korea's KOSPI index. These three markets were chosen because China, Thailand, and South Korea represent countries at varying levels of economic development in Asia, providing strong regional representation. Furthermore, the differences in institutional environments, market structures, and investor behavior among these three stock markets facilitate a multi-dimensional analysis of the similarities and differences in stock index behavior and their appeal to international capital.

The experimental data used daily frequency, covering a long time span. Figs 4(a), 4(b), and 4(c) respectively illustrate the stock index price trends of the three markets. As can be seen from the figures, while all three markets exhibit a certain degree of volatility, they exhibit different trend characteristics and market dynamics. Table 1 summarizes the statistical characteristics of the three sets of raw data. It can be seen that the SSEC and SET indices have negative skewness, indicating that their distributions are left-leaning and their tail risks are biased downward, while the KOSPI has positive skewness, indicating a right-leaning distribution. In terms of kurtosis, all three indices are less than the theoretical kurtosis of a normal distribution, exhibiting a flat peak characteristic, meaning that their distributions are relatively flat. Furthermore, the KOSPI index has the largest standard deviation, indicating that its volatility is higher than that of the other two markets. Furthermore, all three indexes pass the ADF test, indicating that the stock index price series are not stationary in a horizontal state.

Table 1. Descriptive analysis of stock index data

	Sample length	Mean	Standard deviation	Skewness	Kurtosis	ADF (P value)
SSEC	2304	3147.736	249.429	-0.186	-0.459	0.000
SET	2308	1524.624	157.607	-0.620	-0.120	0.000
KOSPI	2329	2423.460	344.892	0.511	-0.174	0.000

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Fig. 4(a) The stock price trend of the SSEC

Fig. 4(b) The stock price trend of the SET

Fig. 4(c) The stock price trend of the KOSPI

ISSN: 2692-7608 DOI: 10.6981/FEM.202512_6(12).0008

3.2. Data Normalization

Dimensionlessness, an important data preprocessing technique, eliminates dimensional differences between features by converting data of varying dimensions to a unified scale or mapping data with varying distributions to a specific distribution. This process not only helps accelerate model convergence but also effectively prevents the negative impact of large features on model training. This study uses a classic normalization method to map feature values to the range [0, 1]. The detailed computation procedure is presented as follows. Among them, X_i^* represents the normalized data, X_i refers to the original data, X_{max}, X_{min} denote the maximum and minimum values of the feature.

$$X_i^* = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{17}$$

3.3. Model Evaluation

To assess the effectiveness of hybrid models, this paper introduces three metrics to measure the model's prediction error: RMSE, MAE, and MAPE. Generally, smaller values for these metrics indicate higher model accuracy. Table 2 lists the calculation formulas for each metric. Here, N denotes the number of samples, and $y_i, \hat{y}_i$ represent the true and predicted values, respectively.

Table 2. Model evaluation metrics

	Computational formula
RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$
MAE	$\frac{1}{N}\sum_{i=1}^{N}\lvert y_i - \hat{y}_i\rvert$
MAPE	$\frac{100\%}{N}\sum_{i=1}^{N}\frac{\lvert y_i - \hat{y}_i\rvert}{y_i}$

4. Empirical Process

4.1. Data Decomposition

CEEMDAN, an signal decomposition technique, partitions financial data into multiple IMFs through dynamic noise addition and a layered decomposition strategy. In experiments, the integration order and noise amplitude were set to 250 and 0.05, respectively. This is because a higher integration order effectively reduces mode aliasing in the decomposition results, improving the stability and robustness of the decomposition. A moderate noise amplitude ensures diversity in the noise-assisted decomposition process while preventing excessive noise from interfering with the signal's inherent characteristics. Furthermore, these parameters were selected based on experience and optimization based on previous experimental results to balance decomposition accuracy and computational complexity. The decomposition results for stock price data are shown in Figs 5(a), 5(b), and 5(c). It is evident that the IMFs exhibit a characteristic shift from high-frequency fluctuations to low-frequency trends, indicating the multi-level structure of short-term market movements and long-term patterns.

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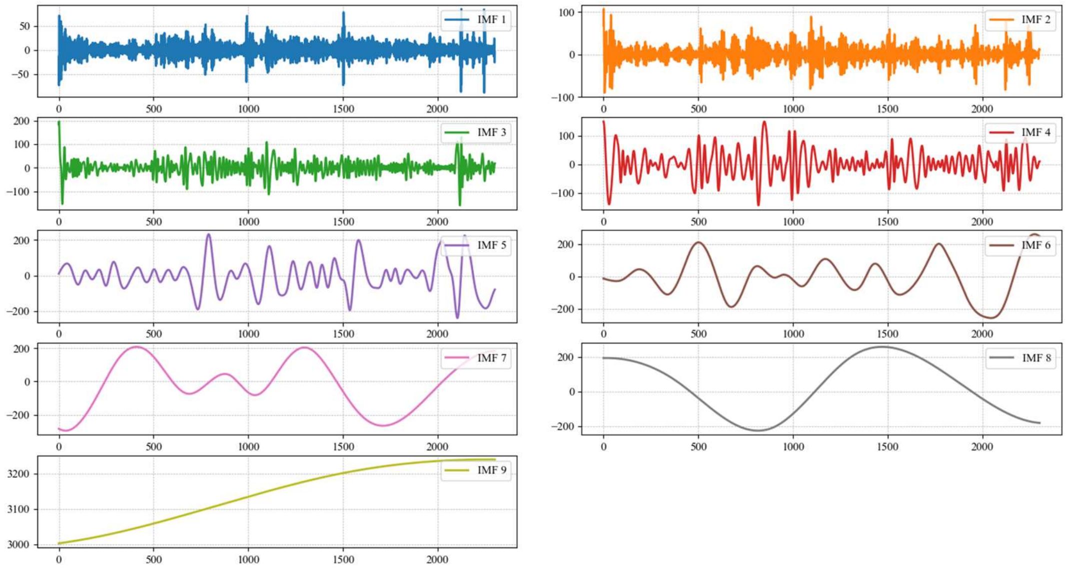

Fig. 5(a) The decomposition result of the SSEC

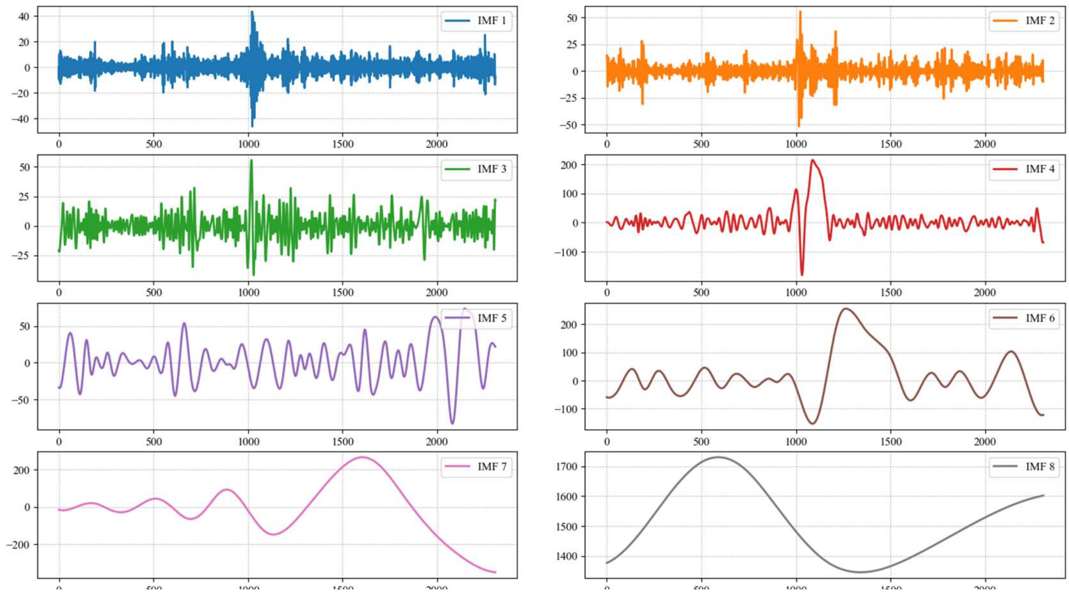

Fig. 5(b) The decomposition result of the SET

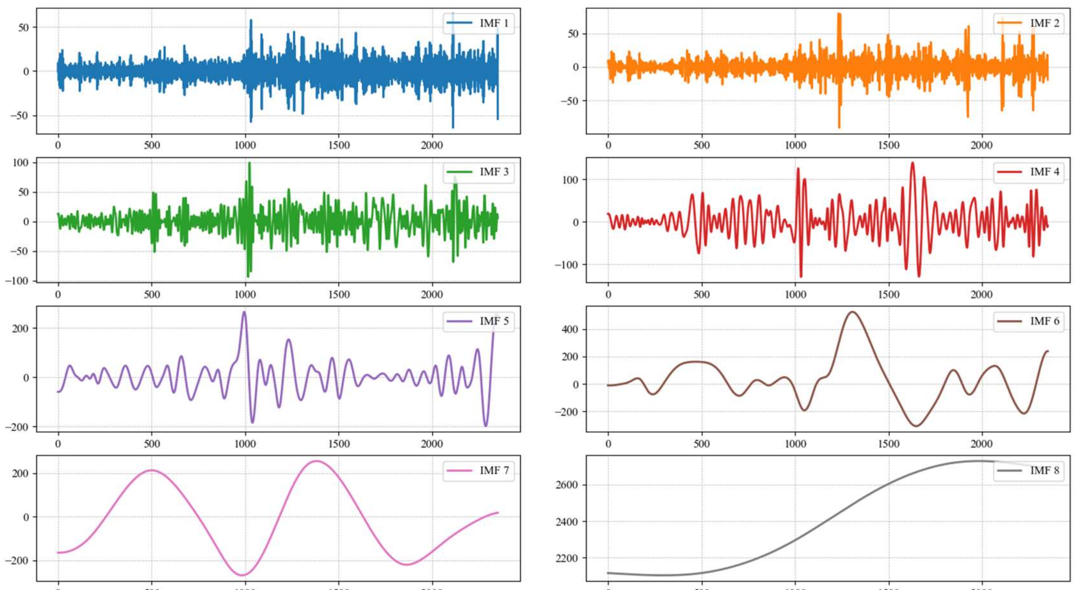

Fig. 5(c) The decomposition result of the KOSPI

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4.2. Prediction Model Training

In financial time series modeling, the GRU is widely used due to its strong modeling capabilities and low computational complexity. However, the traditional GRU structure only considers unidirectional temporal dependencies, making it difficult to fully exploit the potential forward and backward correlations within the series. To address this issue, this paper introduces the BiGRU model to capture both forward and backward dependencies in the series, improving the model's ability to represent market fluctuations.

In the experiment, the basic parameters of the BiGRU are set as shown in Table 3. The number of iterations is 200, and the batch size is 64 to ensure that the model fully learns the time series features. The mean squared error (MSE) loss function accurately measures the deviation between the predicted result and the true value. The Adam optimizer is selected, which combines momentum and an adaptive learning rate strategy to accelerate convergence and improve training stability. Regarding the network structure, the number of fully connected neurons is 32, which is used for further feature transformation. In addition, the model introduces an early stopping strategy to monitor the validation set error. Training automatically stops when the error does not decrease by more than a set threshold after 50 iterations, in order to improve model generalization.

Table 3. Some parameter settings of BiGRU

Hyperparameters	Experimental setup
Number of iterations	200
Batch size	64
Loss function	MSE
Optimization algorithm	Adam
Number of neurons in the fully connected layer	32

4.3. Intelligent Tuning

In addition to the basic model parameters mentioned above, this study also automatically adjusts other hyperparameters in the model through BO. These parameters were chosen for their substantial influence on the model’s training accurately and stability. Specifically, Table 4 lists the parameter settings of the BO: the search space dimension is 3, corresponding to the number of neurons, learning rate, and dropout; the maximum number of optimization calls is set to 30, representing the maximum number of evaluations; and the proxy model is constructed through 5 random sampling points in the initial stage. The acquisition function is gp_hedge, which combines multiple acquisition functions and balances the relationship between exploration and utilization. Table 5 presents the search space of the prediction model hyperparameters and the best parameter combination obtained on the validation set. Based on this, Figs 6 and 7 respectively show the model fitting on the test set and the changing trend of the loss function during training.

Table 4. Bayesian optimization parameter setting

Parameter	Set value
Dimensions	3
N_calls	30
N_initial_points	5
Acq_func	gp_hedge

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Table 5. The Optimal parameter set for three markets

	Search space	Optimal parameter		
		SSEC	SET	KOSPI
Number of neurons	[32,128]	128	99	128
Learning rate	[1e-5,1e-2]	2.486e-3	7.722e-3	3.351e-3
Dropout	[0.15,0.45]	0.15	0.15	0.15

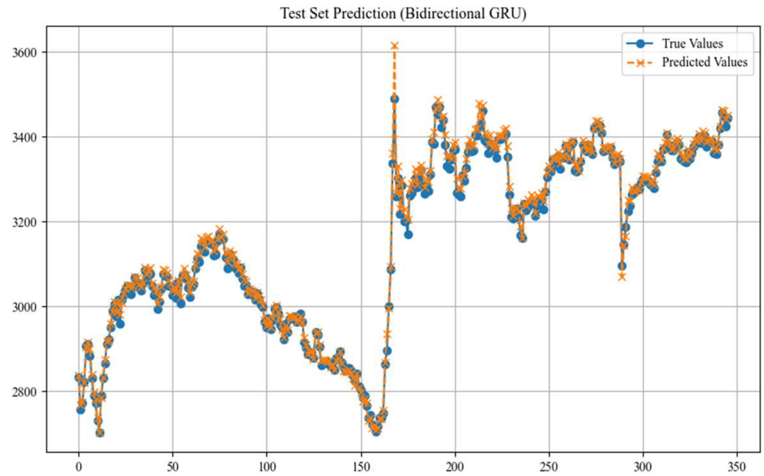

Fig. 6(a) The prediction results of the hybrid model on the SSEC

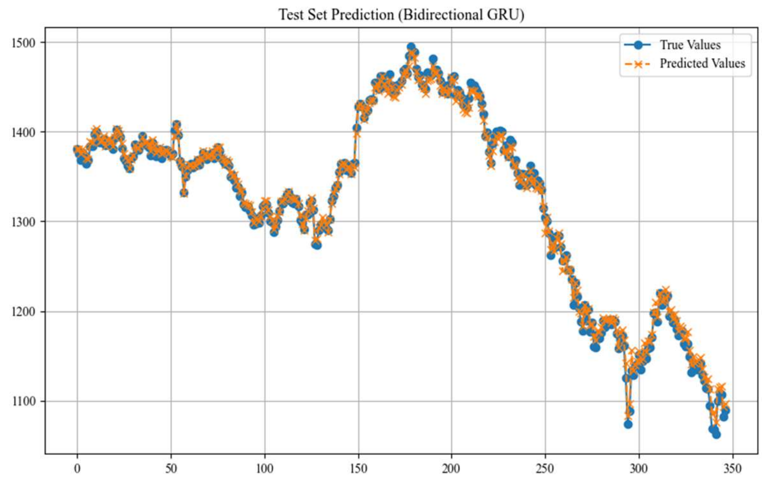

Fig. 6(b) The prediction results of the hybrid model on the SET

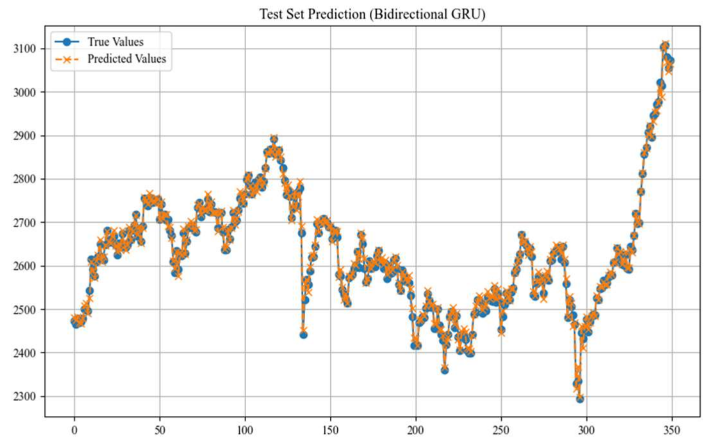

Fig. 6(c) The prediction results of the hybrid model on the KOSPI

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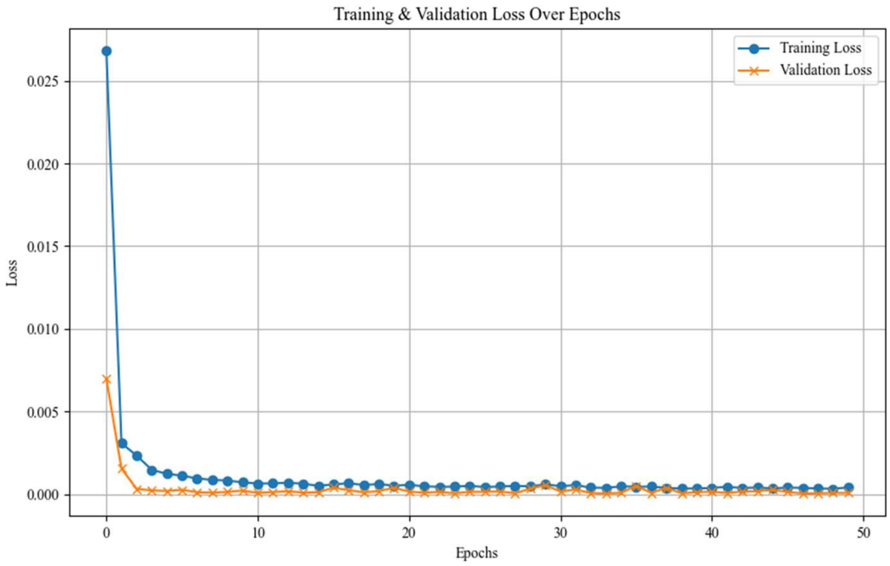

Fig. 7(a) The decline in the loss function of the SSEC

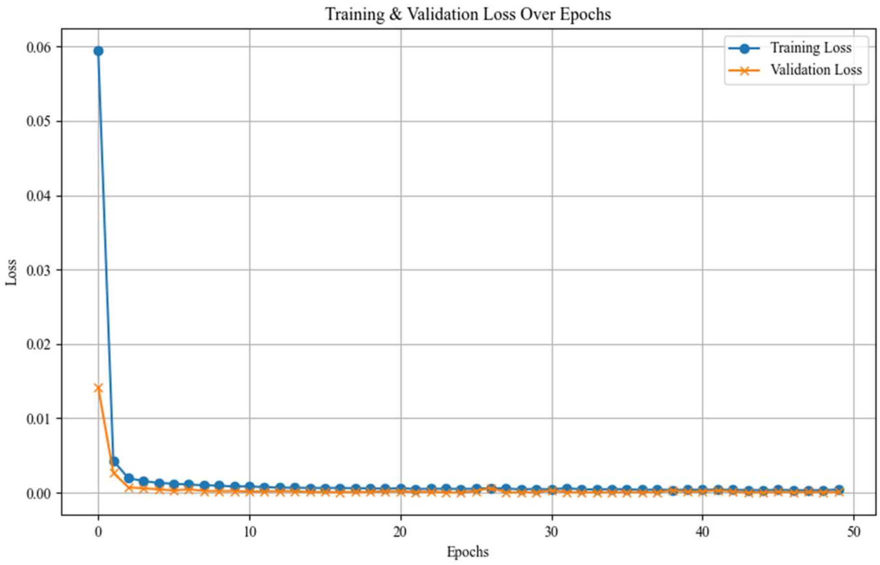

Fig. 7(b) The decline in the loss function of the SET

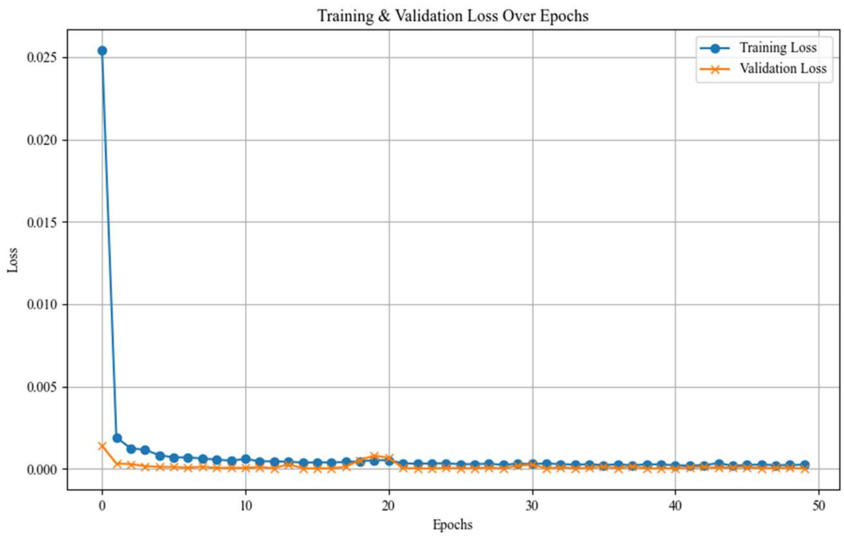

Fig. 7(c) The decline in the loss function of the KOSPI

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4.4. Comparison of Prediction Results

To assess the CEEMDAN-BiGRU-BO model's capability in forecasting financial markets, this study constructed a two-dimensional evaluation system including horizontal and vertical comparisons. Among them, horizontal comparison is conducted to evaluate the forecasting accuracy of different models on the same dataset, and vertical comparison is used to evaluate the performance of the same model under different improvement strategies. Table 6 shows the prediction results of the control model under the two dimensions.

From a horizontal comparison perspective, among a single model, BiGRU demonstrates superior predictive performance compared to XGBoost, RNN, and GRU. Take the MAPE indicator as an example. In the three markets, the BIGRU model achieved 0.228,0.361 and 0.240 respectively, which indicates that BIGRU can better capture the nonlinear features in the data to enhance the prediction accuracy.

Furthermore, the introduction of EMD has clearly confirmed the effectiveness of the hybrid model framework. Take the RMSE indicator as an example. Compared with the BiGRU model, its introduction has reduced the errors by 4.183%, 22,935% and 3.962% respectively. Not only that, the emergence of GS search also enables the model to automatically optimize the optimal parameter combination, thereby enhancing the generalization ability of the model.

Table 6. Comparative model empirical results

			RMSE	MAE	MAPE (%)
SSEC	Horizontal	XGBoost	11.904	8.124	0.259
		RNN	11.832	7.760	0.248
		GRU	11.514	7.819	0.249
		BiGRU	10.806	7.312	0.228
		EMD-BiGRU	10.354	6.986	0.218
		GS-BiGRU	10.360	6.664	0.212
		BiGRU-BO	11.102	6.389	0.202
	Vertical	CEEMDAN-BiGRU	9.777	6.067	0.193
		CEEMDAN-BiGRU-BO	**9.921**	**5.901**	**0.188**
SET	Horizontal	XGBoost	6.875	4.976	0.394
		RNN	7.301	4.809	0.389
		GRU	5.961	4.629	0.362
		BiGRU	7.556	4.453	0.361
		EMD-BiGRU	5.823	4.426	0.345
		GS-BiGRU	5.808	4.301	0.336
	Vertical	BiGRU-BO	5.639	3.886	0.310
		CEEMDAN-BiGRU_BO	**4.773**	**3.735**	**0.291**
KOSPI	Horizontal	XGBoost	8.600	6.752	0.257
		RNN	8.546	6.570	0.251
		GRU	8.728	6.490	0.247
		BiGRU	8.379	6.222	0.240
		EMD-BiGRU	8.047	6.119	0.232
		GS-BiGRU	7.733	5.826	0.223
		BiGRU-BO	7.274	5.555	0.213
	Vertical	CEEMDAN-BiGRU	6.963	5.293	0.203
		CEEMDAN-BiGRU-BO	**6.518**	**4.820**	**0.185**

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In a horizontal comparison, the CEEMDAN-BiGRU-BO model demonstrated the best predictive performance on all three financial market datasets. On the SSEC dataset, the RMSE of this model is 9.921, which is 8.190% lower than that of the basic BiGRU model, and the MAE is 5.901, which is 19.297% lower than that of the basic BiGRU. This improvement in predictive performance also exists in the other two financial markets. Take MAPE as an example. The hybrid model reduced the performance by 6.129% and 8.867% respectively compared to the suboptimal model.

Even more encouragingly, the CEEMDAN-BiGRU-BO model has demonstrated the best performance in the improvement path of the BiGRU series models. On the SET dataset, compared with CEEMDAN-BiGRU, the RMSE of CeemDan-BigRU-BO decreased by 15.357%, the MAE decreased by 3.886%, and the MAPE decreased by 6.129%. This shows the performance improvement brought by the introduction of BO to the hybrid model.

Similarly, on the KOSPI dataset, the RMSE of CEEMDAN-BiGRU-BO is 6.518, which is further reduced by 6.391% compared to BiGRU-BO, and the MAE is 4.820, which is reduced by 8.936% compared to BiGRU-BO. This indicates that the decomposition strategy significantly improves the predictive capability of the model. This phenomenon can also be observed in the SSEC and SET markets, fully verifying the superiority and stability of the CEEMDAN-BiGRU-BO model in the prediction of financial time series.

5. Conclusion

This study combines the advantages of complete ensemble empirical mode decomposition with adaptive noise, bidirectional gated recurrent unit, and Bayesian optimization to develop a novel CEEMDAN-BiGRU-BO prediction model. Experimental analysis on real financial data yields the following conclusions: (1) CEEMDAN effectively decomposes complex time series data into IMF of varying frequencies, improving the model's stability when handling nonlinear and nonstationary data. (2) Compared to traditional GRU models, BiGRU can simultaneously capture forward and backward time series information, improving prediction accuracy. (3) BO algorithms adaptively select optimal parameters based on experimental data, significantly improving model training efficiency. (4) The proposed CEEMDAN-BiGRU-BO prediction model demonstrates the best prediction performance and generalization ability among various control models. Future research will further integrate other multimodal variables to construct a more comprehensive prediction framework and explore how to leverage cutting-edge technologies to further enhance prediction accuracy and efficiency.

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