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A multi-step and multivariate financial time series forecasting framework based on ConvLSTM optimized by Island Algorithm

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Highlights:

- A multi-step multivariate financial forecasting framework based on optimized ConvLSTM is proposed.
- The Island Algorithm automatically tunes ConvLSTM hyper-parameters to reduce manual tuning dependence.
- IA-ConvLSTM achieves superior performance for multi-step-ahead financial multivariate prediction.

Abstract: Multi-scale and multi-indicator financial time series forecasting is a valuable requirement of quantitative analysis and intelligent decision-making. Nevertheless, the current research concentrates on single-step or univariate prediction, which is unable to completely meet the real-life needs of multi-step and multivariate prediction problems in complex financial time-series situations. Convolutional Long Short-Term Memory (ConvLSTM) networks combine convolutional feature extraction with temporal dependency modeling. This combination supports multivariate time series forecasting. Nevertheless, some important hyperparameters like network structure and learning rate are often tuned manually and therefore, it has low parameter configuration efficiency and high reliance on human knowledge. To overcome these challenges, this paper suggests an intelligent financial time series forecasting system that relies on ConvLSTM optimized by Island Algorithm (IA). The Island Algorithm is employed to optimize the important hyperparameters of the ConvLSTM model, including network structure, learning rate, training epochs, and convolution kernel size. By automatically searching for suitable parameter configurations, the proposed framework reduces the dependence on manual parameter tuning and improves the adaptability of ConvLSTM for financial time series forecasting tasks. In addition, three dimensions of evaluation are considered from three perspectives: forecasting performance, reliability of models, and value of practical application, which offer systematic dimensions for evaluating financial time series forecasting frameworks. The proposed method gives a systematic approach to utilize intelligent optimization algorithms to aid deep learning models in financial time series forecasting and provides references for intelligent forecasting applications in various financial scenarios.

Keywords: financial time series forecasting; Island Algorithm; ConvLSTM; hyperparameter optimization; multi-step and multivariate forecasting

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1. Introduction

Quantitative analysis, risk management and intelligent decision-making are all important in financial time series forecasting. As the pace of financial digitalization accelerates, the amount and complexity of financial data have also increased significantly with strong nonlinear and dynamic characteristics. The traditional analysis methods based on expert experience are no longer sufficient to meet modern financial applications. Instead, data-driven forecasting approaches have been gaining popularity. Among them, multi-step and multivariate financial time series forecasting is an effective approach to capture market dynamics and support intelligent decision-making.

The current financial prediction models are based on statistical modeling and machine learning, as well as deep learning. The econometric models like the Autoregressive Conditional Heteroskedasticity (ARCH) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model have been applied to represent the volatility features of the sequence in the field of finance [1,2]. Nevertheless, it is not able to explain complex nonlinearities. As the technology of deep learning has developed, long-term memory networks such as Long Short-Term Memory network have also been used to make predictions in the financial world because they can be trained to recognize long-term dependencies [3,4]. In addition, various machine learning and deep learning methods have been applied to financial forecasting tasks. Support vector machines, artificial neural networks, recurrent neural networks, and other learning-based approaches have shown their ability to capture nonlinear patterns in financial time series. Feature selection and extraction techniques have also been investigated to improve the effectiveness of financial forecasting models [5–9].

Despite the above achievements, there are still some challenges in financial time series prediction. First of all, the existing research is mainly about the single-step or univariate prediction, which cannot meet the needs of multi-step and multivariate prediction. In addition, it is difficult to achieve good results by manual adjustment. In recent years, deep learning methods based on Transformer architectures and frequency decomposition have also been explored for financial and long-sequence time series forecasting [10,11]. The Convolutional Long Short-Term Memory (ConvLSTM) network can be used for multivariate time series prediction. It has the advantages of Convolutional Neural Networks (CNNs) and long short-term memory (LSTM) networks [12,13]. However, how to choose the hyperparameters of the ConvLSTM network is still an open problem.

Intelligent optimization algorithms are a good solution to the problem of automatic hyperparameter configuration of deep learning models. These algorithms can minimize manual adjustment costs and enhance model adaptability by searching optimal parameter combinations. Earlier studies have shown that optimization algorithms, such as Genetic Algorithm (GA), can be used to improve the performance of deep learning models [14]. In addition to GA, optimization algorithms such as Particle Swarm Optimization and other intelligent optimization methods have also been combined with financial forecasting models for parameter optimization and prediction improvement [15–17]. Other meta-heuristic algorithms have also been widely applied to complex optimization problems due to their global search capability [18]. Nevertheless, the performance of optimization algorithms is highly dependent on the quality of parameter search, which may affect the efficiency of hyperparameter optimization.

To solve these problems, a multi-step and multivariate financial time series forecasting framework based on ConvLSTM optimized by Island Algorithm (IA) is proposed in this study. In the proposed

framework, ConvLSTM is used as the forecasting model and the Island Algorithm is used for automatic hyperparameter optimization.

This study makes three contributions. Firstly, an intelligent optimization-based ConvLSTM forecasting framework for multi-step and multivariate financial time series prediction is proposed, which realizes automatic hyperparameter configuration of deep learning models. Secondly, the Island Algorithm is introduced to optimize the important hyperparameters of ConvLSTM and improve the adaptability of the forecasting model. Lastly, an overall evaluation framework is set up to analyze the proposed method from the perspectives of forecasting performance, model reliability, and practical application value.

2. Methods

2.1. ConvLSTM network

Convolutional Long Short-Term Memory (ConvLSTM) is a deep learning model that combines Convolutional Neural Network and Long Short-Term Memory (LSTM). ConvLSTM was originally proposed for modeling spatiotemporal sequences. In contrast to conventional LSTM models where input data is processed using fully connected structures, ConvLSTM substitutes the fully connected operations in state transitions with convolution operations allowing the model to learn temporal dependencies without losing local structural information. Hence, ConvLSTM can be used in multivariate time series forecasting problems. ConvLSTM-based models can be applied to financial forecasting problems and are capable of capturing intricate patterns in high-dimensional financial time series.

The fundamental idea of the ConvLSTM is to apply a convolutional operation and gate recurrent unit. The input data is used to obtain local correlations by the convolution process, whereas the information transmission and update in time is controlled by the gating mechanism. This combination helps ConvLSTM capture cross-variable relationships and temporal dependencies in multivariate financial time series.

The financial time series forecasting process involves the various indicators which are often correlated with each other dynamically and the variations in the market have a strong temporal relationship. To this end, ConvLSTM is used as the primary model of forecasting to extract multivariate features and time patterns of financial time series. Figure 1 shows that input financial time series can be converted into tensor representation, which will then be fed through several layers of ConvLSTM feature extraction, and then the prediction layer will map it to the multi-step forecasts.

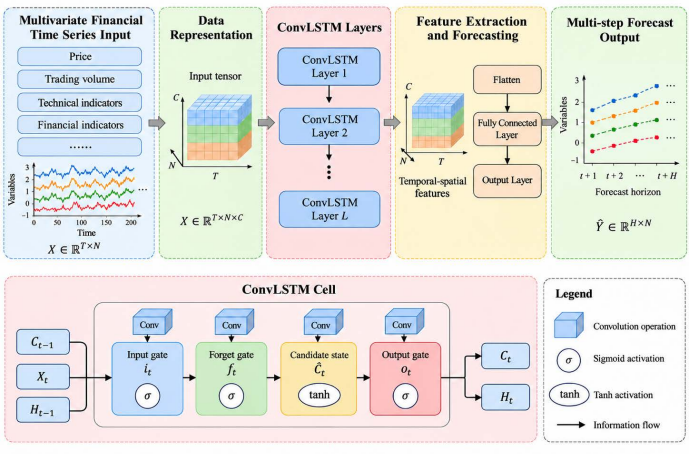


Figure 1. ConvLSTM forecasting framework structure.

2.2. Island Algorithm

Inspired by the evolution process of plant communities on islands in nature, in which plants continuously migrate towards higher altitudes when sea level rises and island area decreases, Ma *et al.* developed a new meta-heuristic optimization algorithm called Island Algorithm [19]. The algorithm imitates the variation in island range, the extinction of plant population and the balance of population during sea-level rise to explore the solution space of optimization problems. Based on its evolution mechanism, Island Algorithm contains mainly three stages: the elimination stage, the sea-level rising stage and the balance stage, as shown in Figure 2.

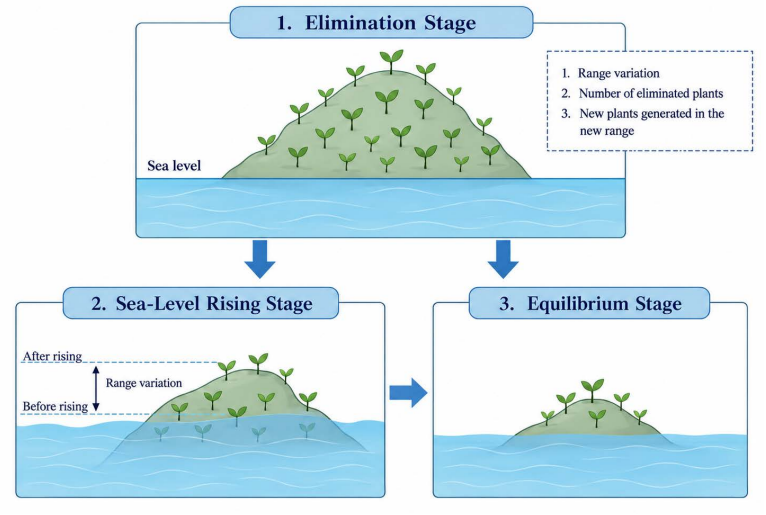


Figure 2. Three-stage diagram of the Island Algorithm.

In the Island Algorithm, it is assumed that each plant in the algorithm is a solution and fitness function is applied to determine the quality of every individual. The elimination stage removes weaker individuals, the sea-level rising stage adjusts the search space, and the balance stage updates individual positions. The three phases are working together in the Island Algorithm to reach an equilibrium between the global exploration and local exploitation, which leads to the gradual development of the more optimal solutions.

The Island Algorithm is used in this study to optimize the most important hyperparameters of the ConvLSTM model such as learning rate, training epochs, number of ConvLSTM layers, and convolution kernel size. The Island Algorithm automatically gets the appropriate parameter configurations of financial time series forecasting tasks by searching various combinations of hyperparameters based on the corresponding model performance. Table 1 summarizes the optimized hyperparameters and their roles.

Table 1. ConvLSTM hyperparameters optimized by the Island Algorithm.

Hyperparameter	Description
Learning rate	Regulates the update step of model parameters in the training process.
Training epochs	Determines the number of complete passes through the training dataset.
Number of ConvLSTM layers	Regulates the depth of the network and temporal feature extraction ability.
Convolution kernel size	Determines the local feature extraction range of convolution operations.

2.3. IA-ConvLSTM forecasting framework

The paper has suggested an IA-ConvLSTM forecasting model in the context of financial time series prediction where Island Algorithm and ConvLSTM have been applied. The framework suggested is based on the intelligent optimization algorithms and deep learning to be used in multi-step and multivariate financial time series predictions. Figure 3 shows the overall structure of the framework.

The original financial time series data are preprocessed in the proposed framework, which involves missing value handling, normalization, and sliding-window construction to produce multidimensional time-series input tensors that can be used by ConvLSTM. The Island Algorithm is then used to optimize the most important hyperparameters of the ConvLSTM model such as learning rate, training epochs, number of ConvLSTM layers, and convolution kernel size.

Once the optimal parameter setup is acquired, ConvLSTM forecasting model is built and trained. ConvLSTM takes local features of financial time series by convolutional operations and temporal dependencies by recurrent structures which allows joint prediction of several related financial indicators.

Lastly, the IA-ConvLSTM model is able to produce outputs in forecasting and will assist in the further analysis of the financial application. The suggested solution combines data pre-processing, smart optimization, deep learning modeling and multi-step prediction into a single process for predicting complex financial time series.

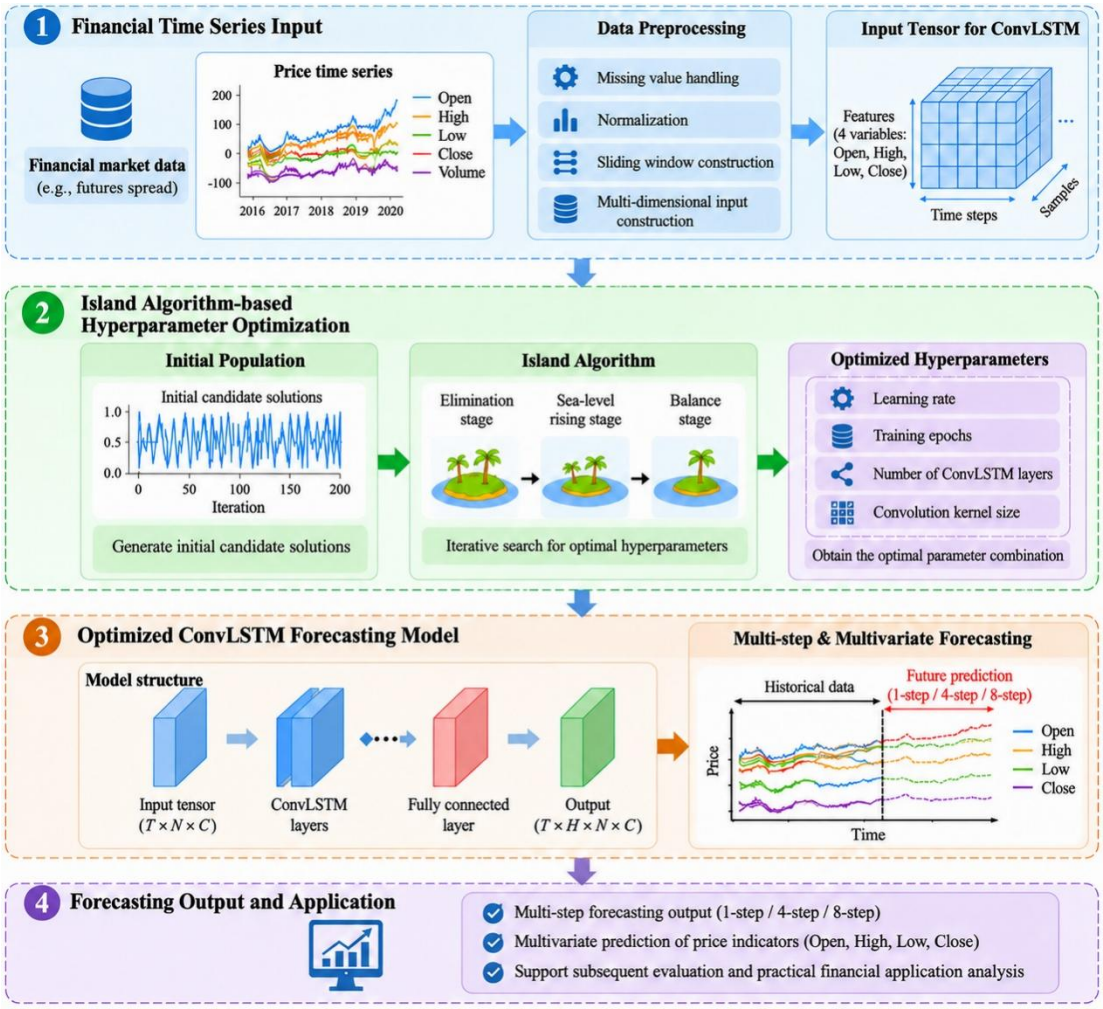


Figure 3. The proposed IA-ConvLSTM forecasting framework.

3. Task design and evaluation specification

3.1. Financial forecasting task design

The suggested IA-ConvLSTM forecasting model is aimed at multi-step and multivariate financial time series prediction. In view of the fact that the data on financial markets have high temporal dependencies and correlations between various variables, this paper develops a forecasting task according to historical price sequences in order to forecast future changes over several time horizons.

In the design of forecasting task, four financial indicators, such as Open, High, Low and Close prices are chosen as prediction variables. Multidimensional time series inputs are built using a sliding-window method, and three scenarios of forecasting, namely short-term, medium-term, and long-term prediction are taken into consideration. In particular, the proposed framework is used to predict future values in 1-step, 4-step, and 8-step horizons.

Different forecasting horizons serve different needs of financial applications. Short-term forecasting targets at immediate market volatility, medium-term forecasting is for short-term trend evolution analysis, and long-term forecasting assesses the ability of the framework to capture market variation patterns in the long run. The detailed design of the forecasting task is given in Table 2.

Table 2. Multi-step and multivariate forecasting design.

Forecast scenario	Forecast horizon	Prediction variables	Application purpose
Short-term forecasting	1-step ahead	Open, High, Low, Close	capturing instantaneous price movements
Medium-term forecasting	4-step ahead	Open, High, Low, Close	Analyzing the evolution of short-term trends
Long-term forecasting	8-step ahead	Open, High, Low, Close	Assessing long-range forecasting capacity

3.2. Multi-level evaluation framework

The assessment of financial time series forecasting models must not be limited to the accuracy of predictions but also model reliability and application value. Thus, this paper develops a multi-level evaluation framework that will be used to analyze the proposed IA-ConvLSTM framework in three aspects: prediction performance, model reliability, and application value as shown in Figure 4.

For the performance evaluation of prediction, some frequently used error metrics are taken into account, such as RMSE, MAE, MAPE and the coefficient of determination (R^2), which are widely adopted for evaluating forecasting accuracy [20]. These indicators reflect the deviation between the forecasting outputs and the real observations from various aspects.

This paper is focused on the reliability of the model, and it includes adaptability of parameters, stability of models, robustness of the model, and generalization ability. As the proposed IA-ConvLSTM architecture involves the Island Algorithm to automatically tune the hyperparameters of the system, the results can be further analyzed in terms of how the intelligent optimization process could adjust the forecasting model based on the financial data features.

When it comes to the value of the application, a prediction system must be not only qualitative but also quantitative in its nature. Hence, the analysis of trend, risk and trading strategy will be considered as one of the significant factors that can be used to assess the potential value of the proposed framework in the study.

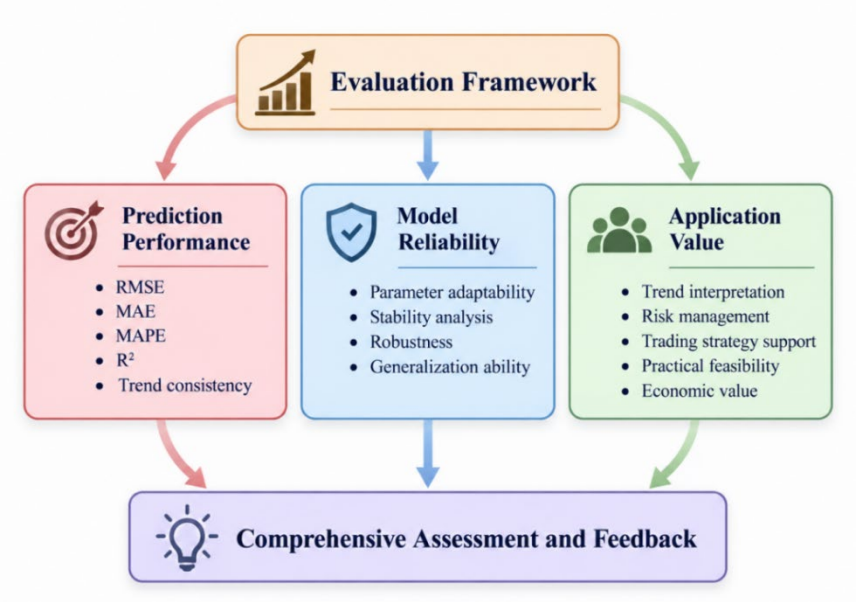


Figure 4. Multi-level evaluation framework for intelligent forecasting.

3.3. IA-ConvLSTM forecasting framework practical application

The IA-ConvLSTM system is a system of forecasting the financial time series data by using deep learning and smart optimization algorithms. In real life, the past financial information was initially converted into multidimensional input of time series. The Island Algorithm then looks at the right ConvLSTM hyperparameter settings to enhance the flexibility of the model structure with the features of the data.

With the optimized parameters, the ConvLSTM model is able to extract local variation features and long-term temporal dependencies from financial sequences simultaneously, and produce future step-ahead forecasting outputs. Such forecasting results could offer additional information for market trend analysis, risk identification, and quantitative investment decision making.

Moreover, the IA-ConvLSTM is also used to provide a financial analysis with the help of multi-variable data and multi-step predictions. It will be able to help in determining market patterns, risks as well as risk evaluation, and offer reference point in making quantitative decisions. In real life, the model can be applied as an intelligent forecasting model to improve the performance of the financial analysis work.

4. Experiments

To validate the effectiveness of the proposed IA-ConvLSTM financial time series forecasting framework, experiments are conducted to evaluate its performance. The experiments mainly consist of two aspects. First, the Island Algorithm is employed to automatically optimize the key hyperparameters of the ConvLSTM model, verifying its effectiveness in improving model parameter configuration. Second, multi-step and multivariate forecasting experiments are conducted by comparing IA-ConvLSTM with other representative deep learning models to evaluate the prediction performance of the proposed framework in financial time series forecasting tasks.

4.1. Experimental setup

The financial time series data used in this study were obtained from the Choice financial terminal, and the original data were sourced from the Shanghai Futures Exchange. The dataset contains historical RB and HC futures trading data, including Open, High, Low, and Close prices. The collected data were processed and organized to construct the dataset used for multi-step and multivariate financial time series forecasting.

The experiments are conducted based on the multi-step and multivariate financial time series forecasting task designed in Section 3. After preprocessing, the dataset is divided into training and testing sets, where the training set is used for model training and hyperparameter optimization, and the testing set is used for performance evaluation.

To comprehensively evaluate the forecasting performance, four metrics are adopted, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). Experiments with different forecasting horizons are conducted to analyze the performance of the proposed model in multi-step forecasting tasks.

4.2. Hyperparameter optimization results

Since the hyperparameter configuration of the ConvLSTM model usually relies on human experience, the manual tuning process is highly subjective and may not always obtain the optimal parameter combination for different financial time series forecasting tasks. Therefore, the Island Algorithm is employed to automatically optimize the key hyperparameters of the model, including the learning rate, training epochs, number of ConvLSTM layers, and convolution kernel size. Table 3 presents the optimized hyperparameter configuration of ConvLSTM obtained by the Island Algorithm.

Table 3. Hyperparameter configuration of ConvLSTM optimized by the Island Algorithm.

Parameter	Search Range	Optimal Value
Learning rate	[0.00001, 0.0005]	$4.84323237 \times 10^{-5}$
Training epochs	[1, 400]	375
Number of ConvLSTM layers	[2, 7]	5
Convolution kernel size	[1, 9]	3

As shown in Table 3, the Island Algorithm obtains an appropriate hyperparameter combination for the ConvLSTM model within the predefined search space. The optimal learning rate is $4.84323237 \times 10^{-5}$, the number of training epochs is 375, and the number of ConvLSTM layers and convolution kernel size are 5 and 3, respectively. The optimized parameter configuration reduces the influence of manual experience-based tuning on model construction and provides a more suitable data-driven configuration for subsequent multi-step and multivariate financial time series forecasting tasks.

4.3. Multi-step and multivariate forecasting results

To verify the effectiveness of the proposed IA-ConvLSTM model in financial time series forecasting tasks, GRU, LSTM, Transformer, and ConvLSTM are selected as comparison models. Among them, GRU and LSTM are representative recurrent neural network models that can effectively capture long-term dependencies in time series data. ConvLSTM further integrates convolutional structures with LSTM,

enabling the extraction of local features and temporal dynamic information simultaneously. By comparing these models, the influence of Island Algorithm optimization on the forecasting performance of ConvLSTM can be analyzed.

The experiments are conducted on four financial indicators, including Open, High, Low, and Close, under different forecasting horizons. Three forecasting scenarios are considered, including 1-step, 4-step, and 8-step ahead prediction. The forecasting results of different models are presented in Table 4.

Table 4. Performance comparison of different models for multi-step and multivariate forecasting.

Model	Metrics	OPEN			HIGH			LOW			CLOSE		
		One	Four	Eight	One	Four	Eight	One	Four	Eight	One	Four	Eight
GRU	RMSE	2.401	8.506	15.744	2.584	8.907	16.100	3.672	9.534	17.047	2.985	8.560	15.752
	MAE	1.896	7.200	13.467	2.196	7.500	13.737	3.044	8.117	14.588	2.338	7.261	13.494
	MAPE	1.586	6.033	11.374	1.838	6.445	11.873	2.475	6.685	12.104	1.831	6.051	11.385
	R^2	0.998	0.975	0.916	0.997	0.973	0.911	0.995	0.969	0.902	0.997	0.975	0.916
LSTM	RMSE	1.991	8.084	14.913	2.456	7.843	14.493	2.946	8.433	15.571	2.779	8.012	14.596
	MAE	1.546	6.906	12.827	1.832	6.643	12.450	2.391	7.208	13.389	2.129	6.803	12.556
	MAPE	1.260	5.775	10.870	1.484	5.661	10.756	1.888	5.896	11.113	1.638	5.655	10.601
	R^2	0.999	0.978	0.924	0.998	0.979	0.928	0.997	0.976	0.918	0.997	0.978	0.927
Transformer	RMSE	4.833	3.892	4.500	4.513	3.792	4.721	5.582	4.907	4.529	5.013	4.359	4.394
	MAE	4.204	2.825	3.277	3.811	2.641	3.496	4.910	3.881	3.279	4.292	3.275	3.136
	MAPE	3.397	2.099	2.439	3.069	1.897	2.692	3.928	3.002	2.387	3.390	2.488	2.266
	R^2	0.992	0.995	0.993	0.993	0.995	0.993	0.990	0.992	0.993	0.992	0.994	0.994
ConvLSTM	RMSE	5.281	7.465	9.525	4.990	7.920	9.292	5.604	8.245	9.569	5.280	8.052	9.916
	MAE	3.973	5.460	6.980	3.633	5.858	6.651	4.206	6.174	6.969	3.890	5.957	7.239
	MAPE	2.877	3.813	4.927	3.556	4.119	4.680	2.817	4.061	4.627	2.663	3.997	4.846
	R^2	0.991	0.981	0.970	0.992	0.979	0.971	0.990	0.978	0.970	0.991	0.978	0.967
IA-ConvLSTM	RMSE	2.906	4.193	5.335	2.601	4.260	5.284	2.748	4.004	5.327	2.852	3.963	5.529
	MAE	2.367	3.305	3.888	2.009	3.309	3.776	2.209	3.109	3.856	2.289	3.035	4.049
	MAPE	1.920	2.664	2.722	1.671	2.707	2.684	1.750	2.402	2.647	1.815	2.317	2.854
	R^2	0.997	0.994	0.991	0.998	0.994	0.991	0.997	0.995	0.991	0.997	0.995	0.990

As shown in Table 4, IA-ConvLSTM achieves improved forecasting performance among the comparison models. Compared with GRU, LSTM, Transformer, and the basic ConvLSTM model, IA-ConvLSTM obtains lower prediction errors in most forecasting scenarios, indicating that the proposed framework can effectively combine convolutional feature extraction, temporal dependency modeling, and intelligent hyperparameter optimization for multivariate financial time series forecasting.

Furthermore, compared with the basic ConvLSTM model, IA-ConvLSTM achieves better performance in terms of RMSE, MAE, and MAPE. This demonstrates that the Island Algorithm can effectively optimize the key hyperparameters of ConvLSTM and improve the adaptability of the forecasting model.

In addition, the prediction difficulty increases with the extension of forecasting horizons. The prediction errors generally increase in longer forecasting scenarios due to the accumulation of uncertainty. However, IA-ConvLSTM still maintains stable forecasting performance, demonstrating its capability in multi-step financial time series prediction.

To further illustrate the forecasting capability of the proposed IA-ConvLSTM model, the prediction results of the Close price are visualized under different forecasting horizons. Since the Close price can effectively reflect the overall market trend, it is selected as a representative indicator for visualization. Figures 5–7 show the comparison between the actual values and predicted values under 1-step, 4-step, and 8-step forecasting tasks.

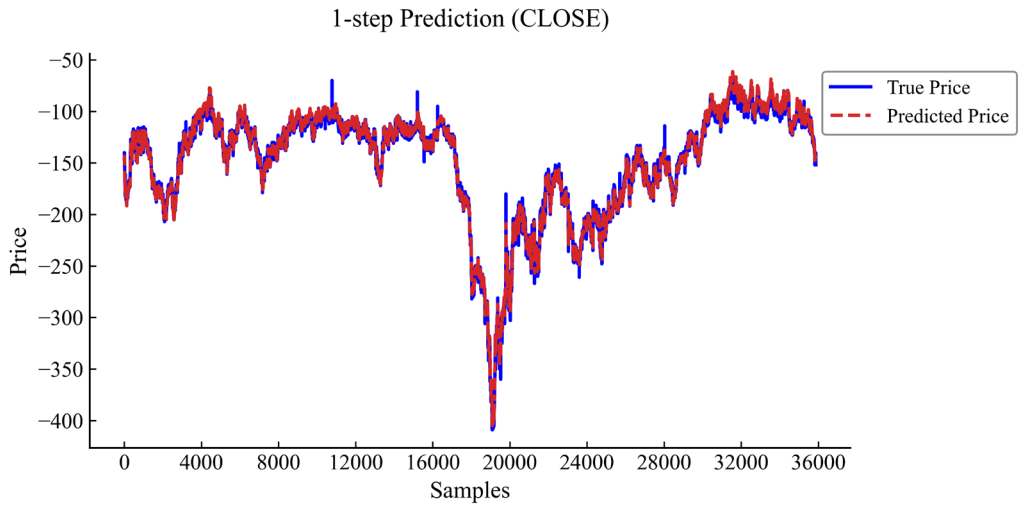


Figure 5. 1-step ahead forecasting results of Close price.

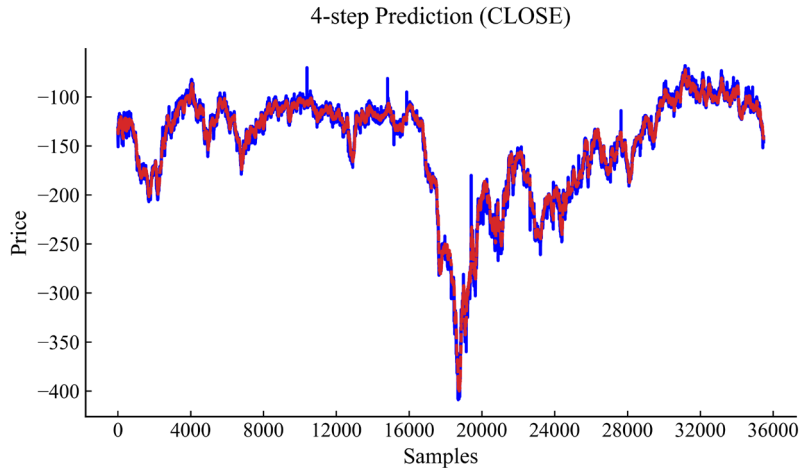


Figure 6. 4-step ahead forecasting results of Close price.

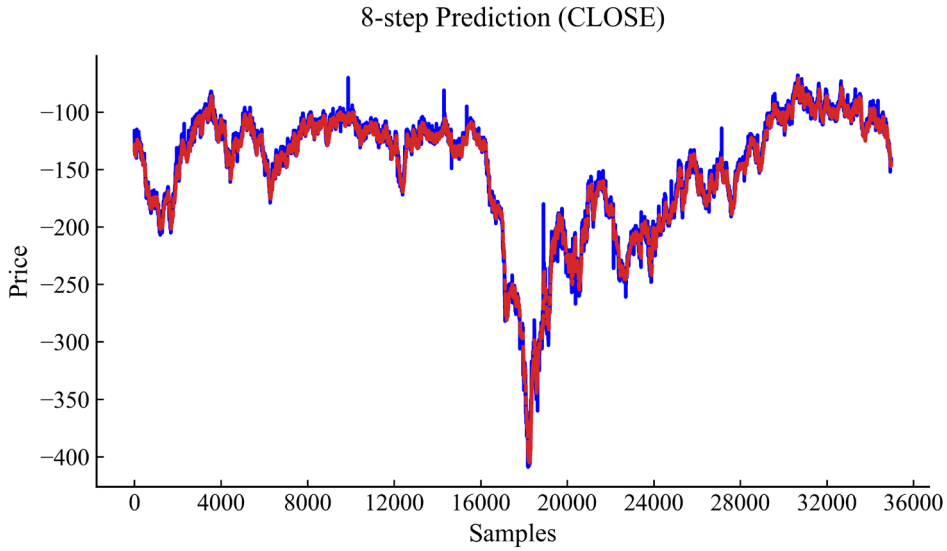


Figure 7. 8-step ahead forecasting results of Close price.

As shown in Figure 5, the predicted Close price closely follows the actual values in the 1-step forecasting scenario, indicating that IA-ConvLSTM can effectively capture short-term fluctuations. Figure 6 presents the 4-step forecasting results. The predicted values maintain a similar trend with the actual values, demonstrating the model's ability to capture temporal dependencies. Figure 7 shows the 8-step forecasting results. Although some deviations appear with longer forecasting horizons, the model still captures the overall trend of financial time series.

5. Conclusion

The present paper presents the IA-ConvLSTM forecasting system, which is a financial time series prediction method based on the Island Algorithm and ConvLSTM model. Compared with the unoptimized ConvLSTM, IA-ConvLSTM achieves lower RMSE, MAE, and MAPE and higher R^2 across the evaluated forecasting horizons and prediction variables.

In contrast to conventional forecasting techniques, the proposed framework takes into account temporal dependencies and multivariate correlations in financial data, offering a systematic approach to complex financial time series prediction tasks. Furthermore, an overall evaluation framework is established, encompassing prediction performance, model reliability, and application value, to facilitate analysis and practical application of intelligent forecasting models.

We would like to point out that the financial market is very dynamic and uncertain, and no prediction model can completely overcome the limitations of financial forecasting. Thus, the IA-ConvLSTM framework is mainly designed as an intelligent analysis and decision support tool instead of a complete replacement of human judgement. In the future, we will work on multi-source data fusion, lightweight model design, and more efficient optimization strategies to further enhance the practicality of intelligent financial forecasting methods.

Data availability statement

The financial time series data were obtained from the Choice financial terminal, and the original data were sourced from the Shanghai Futures Exchange. The processed RB-HC futures spread dataset used in this study is available from the corresponding author upon reasonable request, subject to the data usage policies of the data provider.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used OpenAI ChatGPT (GPT-5.6 Sol) and its integrated image-generation and image-editing functions only to enhance the visual presentation of Figures 1–4. All scientific content, figure layouts, and text labels were designed and provided by the authors. These tools were used solely for visual enhancement and not for scientific content generation. The authors take full responsibility for the content of the manuscript.

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Authors' contribution

Conceptualization, Y.L.T. and Y.X.; methodology, Y.X.; software, Y.X.; validation, Y.X., Y.L.T. and P.K.Q.; formal analysis, Y.X.; investigation, Y.X.; resources, Y.L.T.; data curation, Y.X.; writing—original draft preparation, Y.X.; writing—review and editing, Y.L.T. and P.K.Q.; visualization, Y.X.; supervision, Y.L.T.; project administration, Y.L.T.; funding acquisition, Y.L.T. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

Yongli Tang holds the position of Editorial Board Member for *Advanced Information and Communication* and has not peer reviewed or made any editorial decisions for this paper. The authors declare no other conflicts of interest.

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