Finance Research Letters 69 (2024) 106136

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Revolutionizing Bitcoin price forecasts: A comparative study of advanced hybrid deep learning architectures☆

Xiangyi He [a], Yiwei Li [b], Houjian Li [a,*]

[a] College of Economics, Sichuan Agricultural University, Wenjiang District, Chengdu 611130, China
[b] Essex Business School, University of Essex, United Kingdom

ARTICLE INFO

Keywords:
Bitcoin price
Price forecast
Meta-heuristic optimization algorithms
Hybrid models

ABSTRACT

This paper employs a deep learning network with a comprehensive architecture to forecast Bitcoin prices, enhancing accuracy by integrating two meta-heuristic optimization algorithms, INFO and NRBO. Empirical results demonstrate that the hybrid model significantly outperforms the LSTM in both fit and predictive accuracy across in-sample and out-of-sample data. Notably, the NRBO-CNN-BiLSTM-Attention model substantially improves accuracy in 5-day and 15-day forecasts, reducing the MAPE by over 50 % compared to the LSTM model, thereby significantly enhancing overall predictive performance. The robustness of our results is supported by the MCS tests. Furthermore, strategically modifying time steps in data analysis optimizes model performance.

1. Introduction

Bitcoin, a decentralized digital currency based on blockchain technology, has been a prominent topic in financial technology since its introduction in 2008. The significant price volatility of cryptocurrencies is a defining characteristic of the cryptocurrency market (Risius and Spohrer, 2017; Brauneis and Mestel, 2018). As an essential asset class in global finance, Bitcoin has revolutionized various investment and trading strategies. However, the recent severe volatility in Bitcoin prices has posed significant challenges to the market, drawing the attention of both academic researchers and market participants (Ahmed, 2021; Zeng et al., 2020). Since Bitcoin's volatility is strongly correlated with traditional financial markets, movements in the price of Bitcoin not only affect the decisions of investors and hedgers (Li and Wang, 2017; Patel et al., 2023) but can also lead to pricing errors in Bitcoin derivatives (Liu et al., 2022), potentially triggering volatility in financial markets. The inconsistency of the bitcoin price, the impact of macroeconomic announcements, and the role of market risk factors have been identified as potential mechanisms for triggering volatility in financial markets (Hakim das Neves, 2020; Pieters & Vivanco, 2017; Pyo & Lee, 2020; Troster et al., 2019). Consequently, a deep understanding, modeling, and prediction of Bitcoin's price are crucial for portfolio optimization, risk management and the minimization of potential financial losses (Li et al., 2022).

In current academic research, scholars have employed empirical asset pricing theory to analyze the various factors affecting Bitcoin prices. Several factors contribute to Bitcoin's price trends and volatility, including supply-demand dynamics (Buchholz et al., 2012),

☆ Funding for this research from National Social Science Foundation of China with ratification number 21BGL022 is gratefully acknowledged. We would like to thank the anonymous reviewers for their kind comments and valuable suggestions.

* Corresponding author.
E-mail addresses: 202103260@stu.sicau.edu.cn (X. He), yiwei.li@essex.ac.uk (Y. Li), 14159@sicau.edu.cn (H. Li).

https://doi.org/10.1016/j.frl.2024.106136
Received 30 April 2024; Received in revised form 7 August 2024; Accepted 16 September 2024
Available online 17 September 2024

Table 1
Descriptive statistics.

Variable	Obs.	Mean	Median	S.D.	Min	Max
Opnprc	2923	18521	10340	17337	415.6	73067
Clsprc	2923	18544	10342	17360	415.6	73066
High	2923	18979	10614	17772	416.9	73741
Low	2923	18032	10071	16872	412.4	71338
Vol	2923	204678	106600	228347	260	999530
Pct_change	2923	0	0	0.0400	-0.390	0.260
MA	2923	18207	10236	16916	414.0	68115
EMA	2923	18217	10327	16867	415.1	66342
OBV	2923	1.430e+07	1.660e+07	6.247e+06	3.487e+06	2.510e+07
MACD	2923	155.8	18.36	1114	-5068	5501
signal	2923	147.1	16.72	973.8	-3675	4382
PSAR	2923	17553	9435	15860	392.1	53750
GRPD	2923	104.0	95.46	55.06	3.570	540.8
EPU	2923	138.6	109.6	104.0	4.050	1026
Goldprc	2923	1739	1779	236.9	1174	2250

trading volume (Feng et al., 2018), daily price fluctuations (Baek and Elbeck, 2015), trade adoption (Hakim das Neves, 2020), the Economic Policy Uncertainty Index (Wang et al., 2019), and technical, scale, and momentum effects (Bâra and Oprea, 2024). These factors, intrinsic to Bitcoin's unique nature, significantly shape its market behavior.

Forecasting Bitcoin prices requires the utilization of a variety of analytical techniques, each offering distinct insights. The traditional econometric models, such as ARIMA and GARCH, predict future values by examining historical trends, seasonality and volatility (Aras, 2021; Malladi and Dheeriya, 2021; Xia et al., 2023). Recently, advances in machine learning and artificial intelligence have profoundly influenced academic research. Advanced algorithms such as ANN, Fb-Prophet, and LSTM have been widely employed to analyze large datasets, revealing intricate nonlinear relationships to enhance prediction accuracy (Cheng et al., 2024; Ahmad et al., 2018; Wang et al., 2022; Chen et al., 2017). For instance, Mallqui and Fernandes (2019) employed ANN and SVM, demonstrating a 10 % improvement in predictive accuracy through machine learning models. Ortu et al. (2022) utilized four deep learning algorithms—MLP, CNN, LSTM, and attention LSTM— to assess and forecast price fluctuations, significantly enhancing the predictive precision of all algorithms by integrating various trading and technical indicators. Comparative analyzes have shown that nonlinear deep learning methods outperform traditional ARIMA models (McNally et al., 2018; Phaladisailoed and Numnonda, 2018).

However, current academic models for Bitcoin price prediction remain relatively simplistic. Given that Bitcoin prices are influenced by a variety of complex factors and are highly volatile, simple prediction models often struggle to accurately capture their price movements. While deep learning can capture non-linear features, few academics have proposed models to predict the price of bitcoin using deep learning methods. An effective solution is the use of deep learning architectures capable of multi-level nonlinear operations. Based on prior research, this paper utilizes the LSTM as the foundational prediction model and further explores the use of CNN-BiLSTM and CNN-BiLSTM-Attention as composite machine learning methods for predicting Bitcoin prices. Given the sensitivity of deep learning models to parameter selection, this study introduces the INFO optimization algorithm (Ahmadianfar et al., 2022) to optimize the CNN-BiLSTM model and employs the Newton-Raphson Backpropagation Optimizer (NRBO) (Sowmya et al., 2024) to optimize the CNN-BiLSTM-Attention model. Through this process, we have developed optimized INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention models for Bitcoin price prediction. Validation through multiple loss functions demonstrates that these composite machine learning approaches significantly outperform the standalone LSTM model. Notably, the CNN-BiLSTM-Attention model optimized with the NRBO algorithm shows a well-balanced performance in both in-sample and out-of-sample predictions, exhibiting the best out-of-sample prediction capability among all models.

2. Data and variables

2.1. Data

We collected Bitcoin data spanning 120 months from April 1, 2014, to April 1, 2024, including daily closing (Clsprc) and opening prices (Opnprc), highest (High) and lowest prices (Low), and trading volume (Vol). These data were obtained from investing.com. In this study, these Bitcoin data serve as the primary transaction variables. Moreover, according to research by Bâra and Oprea (2024), incorporating technical indicators can significantly enhance the accuracy of Bitcoin price predictions. Nouir and Hamida (2023) examined the impact of the Economic Policy Uncertainty Index (EPU) and the Geopolitical Risk Index (GPRD) on Bitcoin volatility, finding that the U.S. EPU and GPRD have a short-term impact, while China's EPU and GPRD have a long-term effect. Xia et al. (2023) also demonstrated that including the EPU in the prediction model significantly improves forecasts of Bitcoin volatility. Research by Jareño et al. (2020) revealed a positive and statistically significant correlation between Bitcoin and gold prices. Consequently, this paper incorporates the GPRD, EPU, and gold spot prices (Goldprc) into the model to enhance its predictive performance. Precise definitions of the variables used in this paper can be found in Table A1 of the online appendix.

Table 2
Hyperparameters of CNN-BiLSTM.

Hyperparameter	Value	Hyperparameter	Value
num-filters	32	filter-size	10 × 1
num-bilstm-layer	2	input-lstm-dim	100
output-lstm-dim	64	L2Regularization	0.001
decay-rate	0.8	optimizer	Adam
learning-rate	0.01	dropout	0.25
miniBatchSize	256	maxEpochs	500

Note: "num-filters" refers to the number of convolutional kernels, "filter-sizes" denotes the various kernel scales used in convolution, "num-bilstm-layer" indicates the number of BiLSTM layers, "lstm1-dim" and "lstm2-dim" represent the dimensions of the first and second unidirectional LSTM layers, respectively. "learning-rate" and "decoration-rate" are optimizer parameters, with the initial learning rate set to 0.01. "miniBatchSize" denotes the batch size, set to 256. Finally, "maxEpochs" specifies the maximum number of iterations, set to 500.

Table 3
Hyperparameters of CNN-BiLSTM-Attention.

Hyperparameter	Value	Hyperparameter	Value
num-convolutional-layers	2	filter-size	3 × 1; 3 × 1
num-fiters	96	num-bilstm-layers	2
num-lstm-dim	6 × 2=12	num-attention-head	3
attention-dim	64	L2Regularization	0.001
activation-function	ReLu	optimizer	Adam
initial-learning-rate	0.01	LearnRateDropFactor	0.1
LearnRateDropPeriod	400	maxEpochs	525

Note: The model comprises 2 convolutional layers, each with a 3 × 1 kernel size and a total of 96 kernels. "num-bilstm-layers" is set to 1 layer with 6 neurons, resulting in a unidirectional LSTM dimension of 12. The global attention mechanism includes 3 layers with an attention dimension of 64. L2 regularization coefficient is 0.001. ReLU is the chosen activation function, and Adam is the optimizer. The initial learning rate, "learning-rate," is 0.01. Learning rate drop factor, "LearnRateDropFactor," is 0.1; learning rate drop period, "LearnRateDropPeriod," is 400; and the maximum number of iterations, "maxEpochs," is 525.

Table 4
Hyperparameter optimization range setting for hybrid neural network models.

Model	Params	Search Scope
INFO-CNN-BiLSTM	Initial learning rate	$[10^{-4},10^{-1}]$
	L2Regularization	$[10^{-6},10^{-1}]$
	Neurons in hidden layer	[6,100]
NRBO-CNN-BiLSTM-Attention	Initial learning rate	$[10^{-3},10^{-2}]$
	L2Regularization	$[10^{-4},10^{-1}]$
	Neurons in hidden layer	[10, 30]

2.2. Technical indicators

The price trends of Bitcoin are analyzed using technical indicators commonly applied in the stock market. This paper incorporates several technical indicators based on the study by Bâra and Oprea (2024) into our model. These indicators include the Moving Average (MA), Exponential Moving Average (EMA), On-Balance Volume (OBV), Moving Average Convergence Divergence (MACD), and Parabolic Stop and Reverse (PSAR). The calculations for these technical indicators are detailed in Appendix B online.

2.3. Descriptive statistics

As illustrated in Table 1, our sample encompasses 2923 observations for all three groups of variables. The closing prices exhibited a range of 415.6 to 73066, with an average of 18544. And the standard deviation of the closing price is 17,360, which reflects the high volatility of the bitcoin price.

2.4. Models

We use the first 70 % of the dataset for training and the remaining 30 % for testing, allowing us to evaluate the models' prediction performance under varying conditions. These models examined include a basic LSTM model, hybrid neural network models (comprising CNN-BiLSTM and CNN-BiLSTM-Attention), and optimized hybrid neural network models (including INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention). All these models use Bitcoin's closing price (Clsprc) as the predictive target, with the other

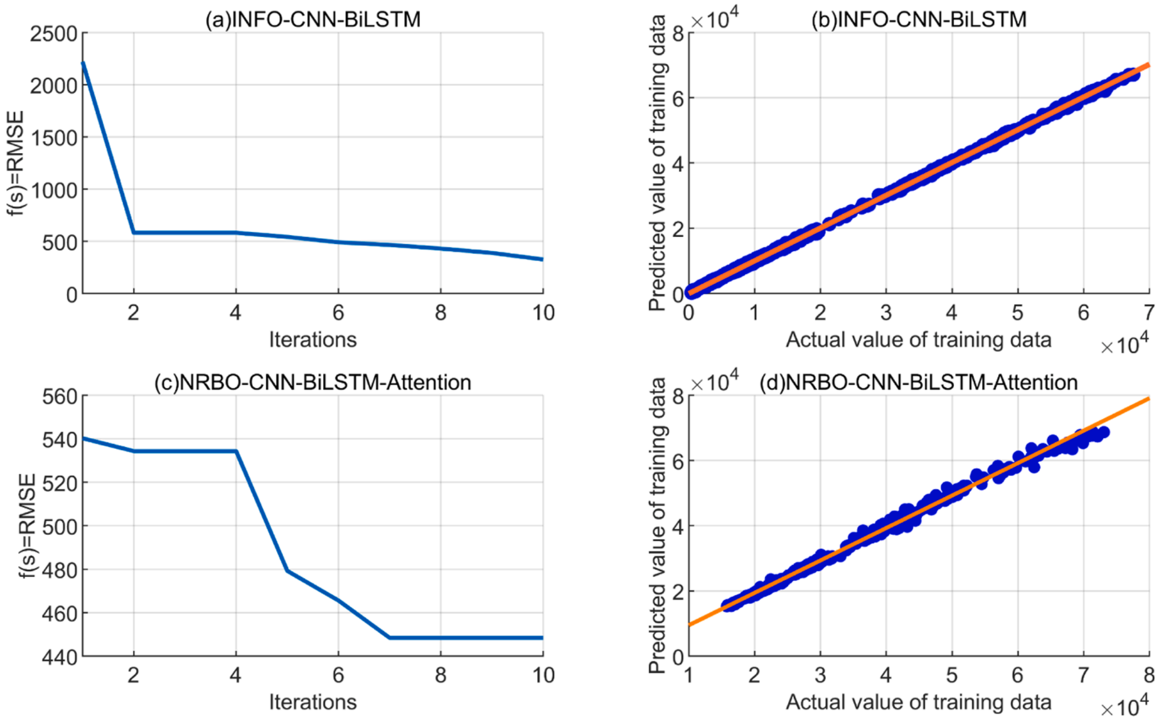

Fig. 1. Iterative curves of the fitness function and their performance in fitting in-sample linearity (5-day step).

variables serving as inputs. Specially, the basic LSTM model consists of two layers: the first layer with 64 neurons and the second layer with 32 neurons, incorporating a dropout rate of 0.2 to mitigate overfitting. The parameters for the hybrid neural network models are detailed in Tables 2 and 3. Table 4 provides the initial ranges for three key hyperparameters adjusted by the optimization algorithms—initial learning rate, regularization coefficient, and the number of nodes in the BiLSTM hidden layers. These optimized parameter settings, consistent with those in Tables 2 and 3, are used for further predictive analysis. Moreover, to explore the impact of different forecasting step lengths on the results, we tested the predictive performance with both 5-day and 15-day step lengths.

2.4. Performance evaluation metrics

In the predictive analysis of time series data using machine learning and deep learning approaches, various loss functions are employed to evaluate the accuracy of the predictive models. This research selects five globally recognized loss functions: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Predictive Residual Error (PRD) and the Coefficient of Determination (R^2). The formulae for these functions are outlined below.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \widehat{Y}_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2} \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right| \times 100\% \tag{3}$$

$$RPD = \frac{\sigma_{observed}}{RMSE} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2} \tag{5}$$

Within this formula, Y_i refers to the actual observed value, $\widehat{Y}_i$ to the value predicted by the model, and n is the number of samples. $\overline{Y}$ refers to the average of the true observations. In addition, $\sigma_{observed}$ is the standard deviation of observed values.

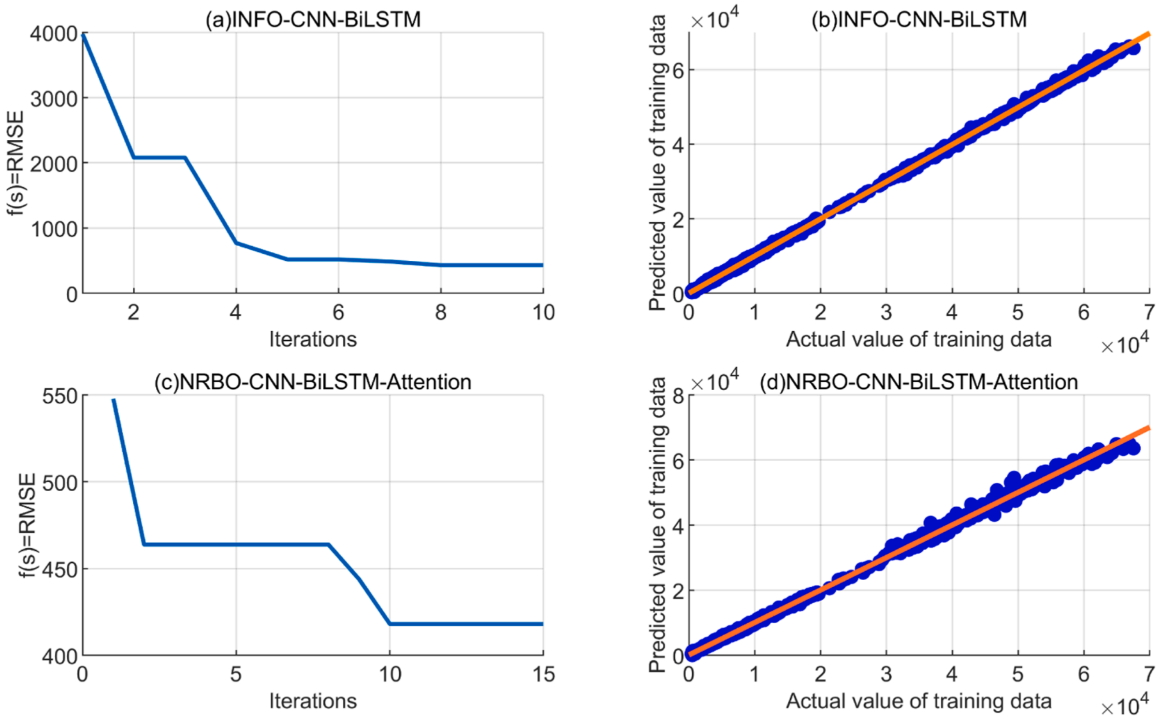

Fig. 2. Iterative curves of the fitness function and their performance in fitting in-sample linearity (15-day step).

Table 5
The best value of 5-day step forecast parameters.

Model	Name of parameter	Best value
INFO-CNN-BiLSTM	Neurons in hidden layer	100
	L2Regularization	1.0000×10^{-6}
	Initial learning rate	3.6834×10^{-4}
NRBO-CNN-BiLSTM-Attention	Neurons in hidden layer	10
	L2Regularization	1.0000×10^{-4}
	Initial learning rate	0.01

Table 6
The best value of 15-day step forecast parameters.

Model	Name of parameter	Best value
INFO-CNN-BiLSTM	Neurons in hidden layer	91
	L2Regularization	1.1056×10^{-5}
	Initial learning rate	3.4918×10^{-4}
NRBO-CNN-BiLSTM-Attention	Neurons in hidden layer	10
	L2Regularization	1.0000×10^{-4}
	Initial learning rate	0.0053

3. Empirical results

To enhance the accuracy and reliability of hybrid neural network models in financial time series forecasting, this study adopted two advanced optimization algorithms, INFO and NRBO, to tune the hyperparameters of the CNN-BiLSTM and CNN-BiLSTM-Attention models. To assess the quality of solutions during continuous iterations, an effective fitness function was employed to select solutions for the optimization objective function. For this time series forecasting problem, this study used the Root Mean Squared Error (RMSE) as the fitness function (f(s)) to evaluate the performance of solutions selected by the optimization algorithms throughout the iterative process.

Table 7
Results of the in-sample forecast with a step size of 5 days. This table shows the fitting performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM and NRBO-CNN-BiLSTM-Attention on the training set. The table includes MAE, RMSE, MAPE, PRD and R^2 on the training set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	1047.993	2433.358	0.180	6.398	0.975
CNN-BiLSTM	993.345	1524.866	0.176	10.222	0.990
CNN-BiLSTM-Attention	492.856	751.737	0.111	23.817	0.997
INFO-CNN-BiLSTM	182.999	249.128	0.039	63.543	0.999
NRBO-CNN-BiLSTM-Attention	472.106	641.286	0.109	30.087	0.998

Table 8
Results of the in-sample forecast with a step size of 15 days. This table shows the fitting performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-CNN-BiLSTM-Attention on the training set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on the training set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	1051.091	2686.904	0.133	5.954	0.969
CNN-BiLSTM	1263.375	1852.818	0.096	8.602	0.986
CNN-BiLSTM-Attention	385.120	554.693	0.074	31.7418	0.998
INFO-CNN-BiLSTM	220.325	307.361	0.038	51.847	0.999
NRBO-CNN-BiLSTM-Attention	285.517	521.227	0.048	30.314	0.998

Table 9
Results of the out-of-sample forecast with a step size of 5 days. This table shows the prediction performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-CNN-BiLSTM-Attention on the testing set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on the testing set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	3815.341	4948.784	0.109	3.209	0.845
CNN-BiLSTM	2098.0857	2552.8682	0.065	5.903	0.958
CNN-BiLSTM-Attention	879.058	1137.193	0.026	13.742	0.991
INFO-CNN-BiLSTM	1987.536	2458.171	0.070	5.560	0.962
NRBO-CNN-BiLSTM-Attention	786.277	995.032	0.025	16.507	0.993

3.1. Determination of optimal parameter combination

Based on the optimal value ranges of three hyperparameters identified in Table 4, we employed an optimization algorithm to determine the best hyperparameter configurations for the hybrid neural network model. Figs. 1 and 2 illustrate the parameter optimization process for the 5-day and 15-day step lengths, respectively. Each row presents the results for one model, showing that the fitting functions of the three models gradually stabilize over the course of iterations. The predictive outputs of all models align closely with the actual observations. Tables 5 and 6 summarize the optimal hyperparameter settings for the two optimized hybrid neural network models under the 5-day and 15-day step length conditions, respectively.

3.2. Forecast results analysis

3.2.1. In-sample forecasting

The predictive performance evaluation results of each model at 5-day and 15-day step lengths are presented in Tables 7 and 8, respectively. These results primarily reflect the models' ability to fit the known data in the training set. By comparing the prediction outcomes across different step lengths, we observed that both the CNN-BiLSTM model and the CNN-BiLSTM-Attention model significantly outperformed the basic LSTM model across all evaluation metrics. This finding aligns with the prevailing view in academia that, although artificial neural networks and their variants can enhance the ability to predict nonlinear features, single artificial intelligence methods may still risk falling into local optima (Movagharnejad et al., 2011; Huang and Wang, 2018). Furthermore, our analysis revealed that the hybrid neural network models exhibited superior in-sample fitting performance after optimizing the parameter combinations.

Further analysis of the data in Tables 7 and 8, comparing the effect of different step lengths on the models' in-sample prediction results, shows that each model fits the actual values more accurately when the prediction window is set to 15 days. In this setting, the INFO-CNN-BiLSTM model exhibits the best fitting capability. Specifically, this model achieves a MAE of 182.999, a RMSE of 249.128, and a MAPE of 0.039 on the training set, while also showing the highest RPD of 63.543 and a R^2 of 0.999. Following closely, the NRBO-CNN-BiLSTM-Attention model shows a MAE of 472.106, an RMSE of 641.286, and a MAPE of 0.109, with an RPD of 30.087 and an R^2 of 0.998. These results indicate that with a longer prediction window, these optimized hybrid neural network models provide a more precise fitting effect.

Table 10
Results of the out-of-sample forecast with a step size of 15 days. This table shows the prediction performance of LSTM, CNN-BiLSTM, CNN-BiLSTM-Attention, INFO-CNN-BiLSTM, and NRBO-CNN-BiLSTM-Attention on the testing set. The table includes MAE, RMSE, MAPE, PRD, and R^2 on the testing set.

Model	MAE	RMSE	MAPE	RPD	R^2
LSTM	3816.414	5035.762	0.126	3.216	0.831
CNN-BiLSTM	1559.070	2433.800	0.044	5.191	0.960
CNN-BiLSTM-Attention	770.665	1014.012	0.026	13.183	0.993
INFO-CNN-BiLSTM	3154.474	3744.785	0.112	3.455	0.907
NRBO-CNN-BiLSTM-Attention	524.576	791.831	0.015	16.038	0.996

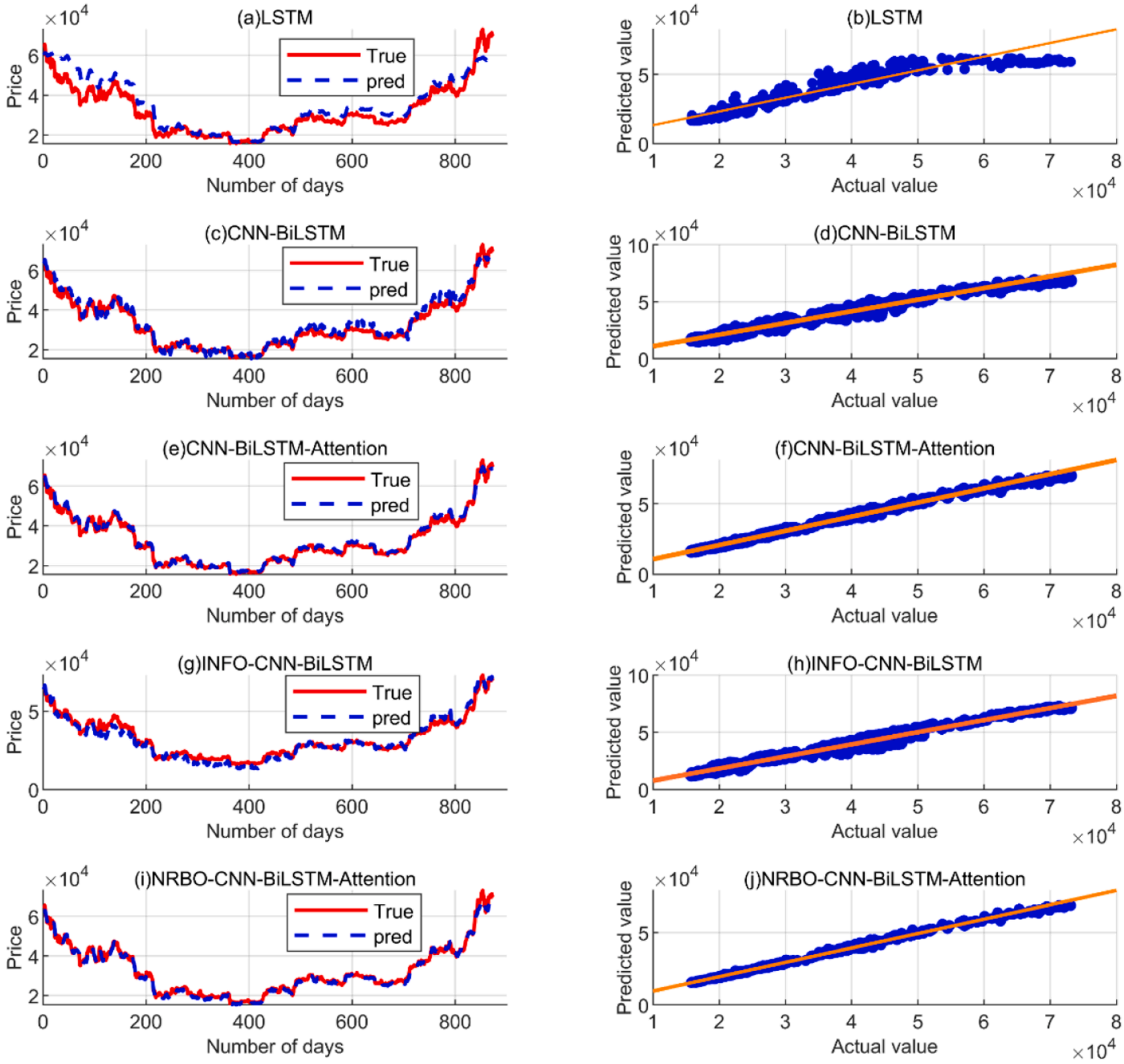

Fig. 3. Out-of-sample predicted performance (5-day step).

3.2.2. Out-of-sample results

Tables 9 and 10 present the out-of-sample prediction performance results for each model at 5-day and 15-day steps, respectively. Figs. 3 and 4 illustrate the prediction performance on the test set. These results enable us to evaluate whether the models can effectively apply patterns learned from the training data to unseen data, thus assessing their generalization capabilities. In both the 5-day and 15-day step length predictions, we find that the hybrid models significantly outperform the standalone LSTM model. Specifically, the NRBO-CNN-BiLSTM-Attention model exhibits the lowest MAE, RMSE, and MAPE on the test set, with 5-day step length results of 786.277, 995.032, and 0.025 respectively; and 15-day step length results of 524.576, 791.831, and 0.015. Additionally, this model also

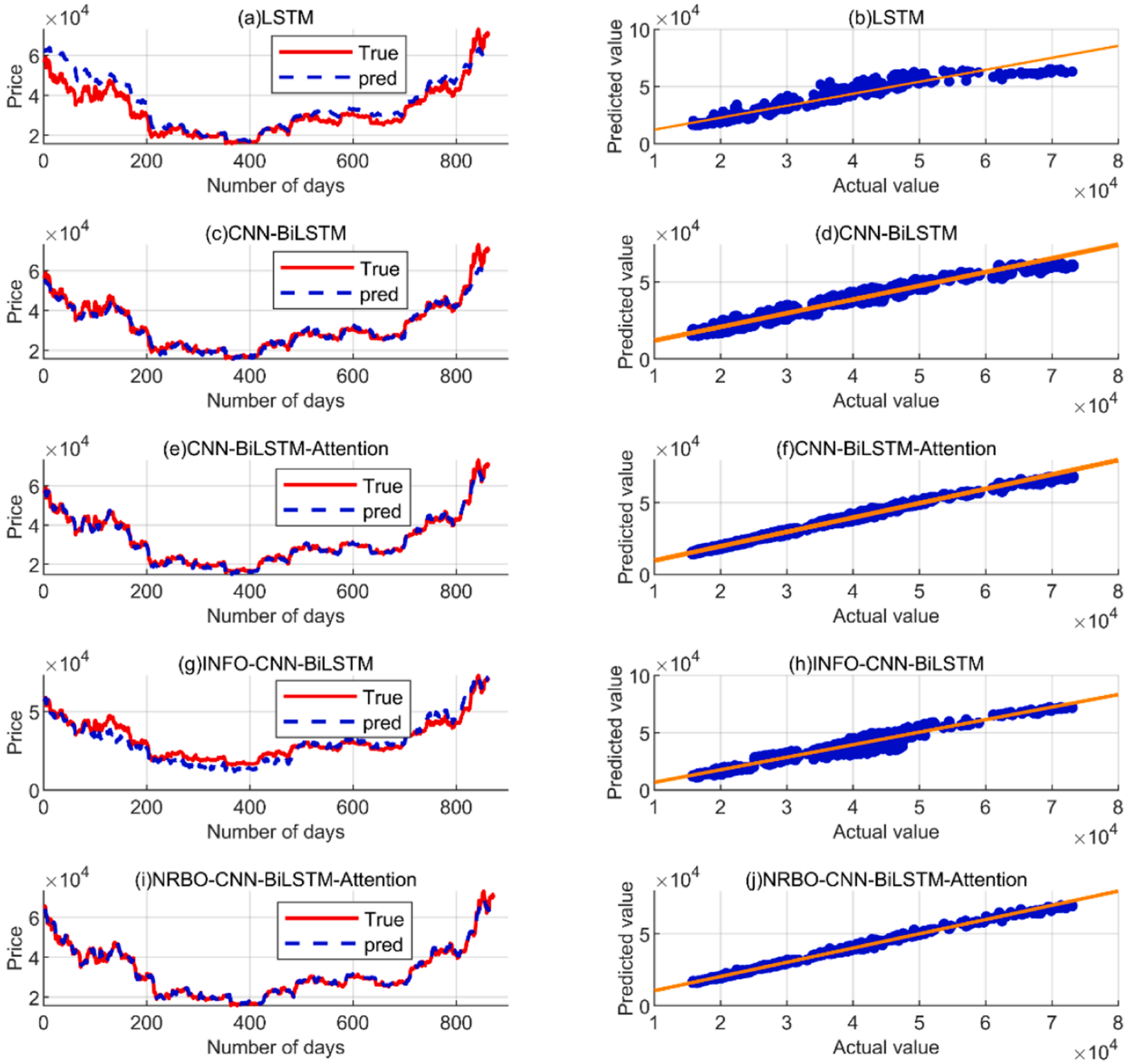

Fig. 4. Out-of-sample predicted performance (15-day step).

shows the highest RPD and R^2, with 5-day step length results of 16.507 and 0.993 respectively; and 15-day step length results of 16.038 and 0.996. Integrating these metrics, the NRBO-CNN-BiLSTM-Attention model demonstrates the strongest out-of-sample predictive capability, effectively addressing the limitations of time series. Following closely are the CNN-BiLSTM-Attention model (MAPE = 0.026) and the CNN-BiLSTM model (MAPE = 0.044). The INFO-CNN-BiLSTM model, while having a test set MAPE of 0.070, still performs better than the CNN-BiLSTM, suggesting potential overfitting issues with the INFO algorithm. Furthermore, a comprehensive assessment of out-of-sample prediction indicators shows that the 15-day step length predictions generally outperform the 5-day step length predictions in terms of accuracy. This suggests that a longer prediction window allows for better capture of the underlying patterns, leading to more precise forecasts.

Furthermore, we employed the Model Confidence Set (MCS) test proposed by Hansen et al. (2005) with a confidence level set at 0.05, as detailed in our Appendix D online. The MCS tests results reveal that under the loss functions of MAE, MSE, and MAPE, the NRBO-CNN-BiLSTM-Attention model exhibits the highest p-values, all equating to 1. This indicates that the NRBO-CNN-BiLSTM-Attention model achieves the highest accuracy in predicting Bitcoin prices. Beyond the deep architecture's proficient feature extraction capability, which captures long-term dependencies and global patterns (Chen et al., 2023), another contributing factor is the NRBO algorithm's utilization of the Newton-Raphson Search Rule (NRSR) and Trap Avoidance Operator (TAO). By integrating the concepts of gradient-based methods with the advantages of population-based optimization approaches, the NRBO algorithm overcomes the limitations of both gradient and non-gradient-based algorithms. This hybrid approach allows it to swiftly refine its search upon identifying promising regions, thereby optimizing model parameters more effectively and enhancing overall model performance.

To verify the robustness of our conclusions, we utilized 5-fold time series cross-validation to evaluate each model's performance on both training and test sets. By comparing the loss functions MAE, RMSE, and MAPE across these sets, we found consistent results with our empirical findings, thereby confirming their robustness. Detailed cross-validation results and a discussion on the causes of overfitting in the INFO-CNN-BiLSTM models are provided in the Appendix D online.

4. Conclusion

This paper employs hybrid deep learning models and their optimized versions to predict Bitcoin prices, comparing the results with the basic LSTM model and exploring the application of complex model architectures in Bitcoin price prediction. Empirical results demonstrate that, for both in-sample and out-of-sample prediction, the fitting and predictive abilities of the hybrid deep learning networks significantly surpass those of the standalone LSTM model. Notably, the NRBO-CNN-BiLSTM-Attention model exhibits a well-balanced performance across all evaluation metrics and shows exceptional predictive capabilities on the test sets for both 5-day and 15-day step lengths. Compared to the LSTM model, the MAPE value decreased by over 50 %, markedly enhancing the prediction accuracy. However, despite the excellent fitting capability of the INFO-CNN-BiLSTM model, its performance on the test set was subpar, likely due to overfitting during the parameter optimization process. This raises questions the effectiveness of the INFO algorithm in optimizing deep learning parameters. Moreover, by comparing the prediction results between 5-day and 15-day step lengths, we suggest that restructuring the dataset by increasing the time step length could be an effective method to improve model prediction performance. In summary, our research finds that the hybrid deep learning model optimized with the NRBO algorithm, NRBO-CNN-BiLSTM-Attention, demonstrates strong potential in Bitcoin price prediction, showing its superiority across various model and parameter configurations.

CRediT authorship contribution statement

Xiangyi He: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Yiwei Li:** Writing – review & editing, Methodology. **Houjian Li:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2024.106136.

References

Ahmad, I., Basheri, M., Iqbal, M.J., Rahim, A., 2018. Performance comparison of support vector machine, random forest, and extreme learning machine for intrusion detection. IEEe Access. 6, 33789–33795.
Ahmadianfar, I., Heidari, A.A., Noshadian, S., Chen, H., Gandomi, A.H., 2022. INFO: an efficient optimization algorithm based on weighted mean of vectors. Expert. Syst. Appl. 195, 116516.
Ahmed, W.M., 2021. Stock market reactions to upside and downside volatility of Bitcoin: a quantile analysis. N. Am. J. Econ. Finance 57, 101379.
Aras, S., 2021. Stacking hybrid GARCH models for forecasting Bitcoin volatility. Expert. Syst. Appl. 174, 114747.
Baek, C., Elbeck, M., 2015. Bitcoins as an investment or speculative vehicle? A first look. Appl. Econ. Lett. 22 (1), 30–34.
Bâra, A., Oprea, S.V., 2024. An ensemble learning method for Bitcoin price prediction based on volatility indicators and trend. Eng. Appl. Artif. Intell. 133, 107991.
Brauneis, A., Mestel, R., 2018. Price discovery of cryptocurrencies: Bitcoin and beyond. Econ. Lett. 165, 58–61.
Buchholz, M., Delaney, J., Warren, J., Parker, J., 2012. Bits and bets, information, price volatility, and demand for Bitcoin. Economics 312 (1), 2–48.
Chen, W., Pourghasemi, H.R., Kornejady, A., Zhang, N., 2017. Landslide spatial modeling: introducing new ensembles of ANN, MaxEnt, and SVM machine learning techniques. Geoderma 305, 314–327.
Chen, Z., Ma, M., Li, T., Wang, H., Li, C., 2023. Long sequence time-series forecasting with deep learning: a survey. Inf. Fusion 97, 101819.
Cheng, J., Tiwari, S., Khaled, D., Mahendru, M., Shahzad, U., 2024. Forecasting Bitcoin prices using artificial intelligence: Combination of ML, SARIMA, and Facebook Prophet models. Technol. Forecast. Soc. Change 198, 122938.
Feng, W., Wang, Y., Zhang, Z., 2018. Informed trading in the Bitcoin market. Financ. Res. Lett. 26, 63–70.
Hakim das Neves, R., 2020. Bitcoin pricing: impact of attractiveness variables. Financ. Innov. 6 (1), 21.
Hansen, P.R., Lunde, A., Nason, J.M., 2005. In: Model Confidence Sets for Forecasting Models, Federal Reserve Bank of Atlanta. Working paper, pp. 2005–2007.
Huang, L., Wang, J., 2018. Global crude oil price prediction and synchronization based accuracy evaluation using random wavelet neural network. Energy 151, 875–888.
Jareño, F., de la O González, M., Tolentino, M., Sierra, K., 2020. Bitcoin and gold price returns: a quantile regression and NARDL analysis. Resour. Policy. 67, 101666.
Li, X., Wang, C.A., 2017. The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. Decis. Support Syst. 95, 49–60.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Finance 77 (2), 1133–1177.
Malladi, R.K., Dheeriya, P.L., 2021. Time series analysis of cryptocurrency returns and volatilities. J. Econ. Financ. 45 (1), 75–94.
Mallqui, D.C., Fernandes, R.A., 2019. Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques. Appl. Soft. Comput. 75, 596–606.
McNally, S., Roche, J., Caton, S., 2018. Predicting the price of bitcoin using machine learning. In: 2018 26th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP). IEEE, pp. 339–343.
Movagharnejad, K., Mehdizadeh, B., Banihashemi, M., Kordkheili, M.S., 2011. Forecasting the differences between various commercial oil prices in the Persian Gulf region by neural network. Energy 36 (7), 3979–3984.
Nouir, J.B., Hamida, H.B.H., 2023. How do economic policy uncertainty and geopolitical risk drive Bitcoin volatility? Res. Int. Bus. Finance 64, 101809.

Ortu, M., Uras, N., Conversano, C., Bartolucci, S., Destefanis, G., 2022. On technical trading and social media indicators for cryptocurrency price classification through deep learning. Expert. Syst. Appl. 198, 116804.
Patel, R., Kumar, S., Bouri, E., Iqbal, N., 2023. Spillovers between green and dirty cryptocurrencies and socially responsible investments around the war in Ukraine. Int. Rev. Econ. Financ. 87, 143–162.
Phaladisailoed, T., Numnonda, T., 2018. Machine learning models comparison for bitcoin price prediction. In: 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE). IEEE, pp. 506–511.
Pieters, G., Vivanco, S., 2017. Financial regulations and price inconsistencies across Bitcoin markets. Inf. Econ. Pol. 39, 1–14.
Pyo, S., Lee, J., 2020. Do FOMC and macroeconomic announcements affect Bitcoin prices? Financ. Res. Lett. 37, 101386.
Risius, M., Spohrer, K., 2017. A blockchain research framework: what we (don't) know, where we go from here, and how we will get there. Bus. Inf. Syst. Eng. 59, 385–409.
Sowmya, R., Premkumar, M., Jangir, P., 2024. Newton-Raphson-based optimizer: a new population-based metaheuristic algorithm for continuous optimization problems. Eng. Appl. Artif. Intell. 128, 107532.
Troster, V., Tiwari, A.K., Shahbaz, M., Macedo, D.N., 2019. Bitcoin returns and risk: a general GARCH and GAS analysis. Financ. Res. Lett. 30, 187–193.
Wang, C., Shen, D., Li, Y., 2022. Aggregate investor attention and Bitcoin return: the long short-term memory networks perspective. Financ. Res. Lett. 49, 103143.
Wang, G.J., Xie, C., Wen, D., Zhao, L., 2019. When Bitcoin meets economic policy uncertainty (EPU): measuring risk spillover effect from EPU to Bitcoin. Financ. Res. Lett. 31.
Xia, Y., Sang, C., He, L., Wang, Z., 2023. The role of uncertainty index in forecasting volatility of Bitcoin: fresh evidence from GARCH-MIDAS approach. Financ. Res. Lett. 52, 103391.
Zeng, T., Yang, M., Shen, Y., 2020. Fancy Bitcoin and conventional financial assets: measuring market integration based on connectedness networks. Econ. Model. 90, 209–220.