A GRU-based hybrid global stock price index forecasting model with group decision-making

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Abstract: To predict the global stock price index daily more effectively, this study develops a new filtering gate recurrent unit group-based decision-making (FiGRU_G) model that combines GRU group network and group decision-making strategy. This proposed FiGRU_G model can effectively overcome the shortcoming of traditional neural network algorithms that the random initialisation of network weights may cause worse performance to some extent. The experimental results indicate visually the proposed FiGRU_G framework outperforms other competing methods in terms of prediction accuracy and robustness for both Chinese and international stock markets. In the short-term prediction scenario, the FiGRU_G framework achieves 20% and 19% performance improvements on evaluation criteria MAPE and SDAPE respectively compared with the GRU model in the Chinese stock market. For the international markets, this FiGRU_G framework also achieves 23% and 22% performance improvements respectively compared with the GRU model.

Keywords: stock closing price prediction; deep learning; GRU model; group decision-making.

Reference to this paper should be made as follows: Hu, J., Chang, Q. and Yan, S. (2023) ‘A GRU-based hybrid global stock price index forecasting model with group decision-making’, *Int. J. Computational Science and Engineering*, Vol. 26, No. 1, pp.12–19.

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1 Introduction

Changes in stock price indexes can be regard as barometers of social and economic developments. Especially, the stock closing price, as one of the most important indexes with significance observation in a trading day, is the primary factor for trading decisions. Stock closing price daily prediction aims at forecasting the future change trends of each stock, which is capable of helping investors judge the macro trend of the stock for making good investment decisions to realise sustainable profit in stock market. What is more, the predicted stock price is also viewed as an important reference for the measurement of social development by many economists and entrepreneurs.

Therefore, the accurate prediction of daily global stock closing price is gaining more attention in recent years.

In comparison to general markets, the stock market is a changeable system with higher volatility, where the closing prices can be viewed as nonlinear time series. Therefore, traditional methods for stock closing price prediction accordingly utilise approaches for time series analysis. Recently, neural networks have been proved to be powerful tools for sequential problem modelling, and it is also introduced and widely used for stock price prediction. Nevertheless, traditional neural network algorithms (Panda et al., 2021; Xi et al., 2021) may generate incorrect predictions as the random selection of initial weight. The existing research shows that current deep learning technology may be prone to predicting the stock price with a higher accuracy than the neural networks of the past (Song et al., 2019; Wu et al., 2021; Hu, 2021). In addition, most existing deep-learning-based method does not take the robustness of the prediction as optimising goals (Hu, 2021; Wang et al., 2021). Specifically, researches pay more attention to foreign stock markets [e.g., the Nasdaq index and the Standard & Poor (S&P) index], while stock markets in developing countries, (e.g., Shenzhen stock index), have not received enough attention. Thus, the robustness of the prediction is not significant in China and Foreign market stocks.

To tackle issues mentioned above, a novel deep-learning-based model, named FiGRU_G model is proposed for global stock closing price prediction. The advantages of the proposed framework are in two major aspects:

1. developing a hybrid global stock closing price daily forecasting model in order to select the stock with the highest expected return according to the stock closing price
2. capturing the daily fluctuation trends of the global stock closing price in both China market and foreign market stocks.

Briefly, the major contributions of this study include two aspects.

1. A powerful hybrid FiGRU_G framework for daily prediction of global stock closing price with nonlinear features is proposed. This model combines the GRU group module and a group decision-making regression module. It can obviously reduce the interference of random selection of initial weight in traditional neural network algorithms.
2. The stock market studied involves both China and foreign markets which have different fluctuation characteristics.
3. The FiGRU_G approach is compared with MLP, CNN, LSTM, GRU, BaGRU_G and FcGRU_G models on the collected datasets from representative stock price indexes of China and foreign live stock markets. The experimental results indicate visually the proposed FiGRU_G framework outperform other competing methods in prediction accuracy and robustness for global stock markets.

The rest of this paper is organised as follows. Section 2 presents the related work about stock price index prediction. The proposed framework in detail is introduced in Section 3. Section 4 provides data collected from the live global stock market. Section 5 gives the experimental results for stock closing price prediction of the FiGRU_G framework and competing methods. In the end, this paper is concluded and the future work is indicated.

2 Related work

It is demonstrated that machine learning methods can be used to predict financial market and achieve better performance (Hsu et al., 2016). Recent work on stock prediction using machine-learning-based methods can mainly be divided into two kinds, i.e., price regression, trend classification. For price regression, Bao et al. (2017) fed historical stock closing prices into an LSTM network to forecast the daily ahead closing price. Alberg and Lipton (2017) combined of multi-layer perception and an LSTM to make the trend prediction of fundamental indicators for a stock. For trend classification, Nguyen and Shirai (2015) proposed a support vector machine to classify the trend of each stock. Later, the historical and current data are both used for predicting the future trend of the stock. For example, Adhikari and Agrawal (2014) integrated a random walk and an ANN to predict stock price indices. Wang and Wang (2017) applied the empirical mode decomposition algorithm and stochastic time neural networks to make predictions.

Although the above neural networks perform well in prediction, their accuracies are just passable when modelling nonlinear time series data (Das et al., 2016). Recurrent neural network (RNN) is especially suitable for modelling such nonlinear time series data by before-after association (Hajiabotorabi et al., 2019), and many works based on RNN has been developed in financial time series forecasting (Wang et al., 2019). RNN models the dependencies of stock price at different time steps with its connected hidden cell. However, the historical information in RNN would accumulate with increase of time horizon, probably causing gradient disappearance or explosion and making the model hard to be trained. To tackle this, LSTM network with the memory cell structure is introduced. This structure can filter out historical information that is unimportant, and ensure the previous information preserved in network internal state (Fischer and Krauss, 2018). More specially, GRU network is a nice variant of the LSTM that is simpler in structure and works better than LSTM. Lee and Yoo (2020) studied the different performance of RNN, LSTM and GRU in stock price prediction. Shen et al. (2018) improved GRU networks to predict trading signals for stock indices. But these single models still have deficiencies in the application of complex stock price index prediction, such as low accuracy and stability.

Hybrid models integrating several single models have been introduced to overcome above disadvantages, which can capture various patterns of the raw data to jointly make better decision (Kim and Won, 2018). The decomposition-ensemble method is a popular hybrid approach following the principle of divide-and-conquer (Zhou and Fujita, 2017), which decomposes the raw data into a few numbers of independent subseries, and the prediction can adaptively extract the features of each subseries. Lu (2017) introduced an EMD-RBF framework for stock index prediction and achieved competitive results. Yang and Lin (2016) proposed a model integrating EMD, ARIMA and SVR for stock forecasting. Significantly different from EMD, variational mode decomposition (VMD) can decompose raw series into many components, which perform better in noise robustness and component decomposition (Upadhyay and Pachori, 2015). VMD has been successfully applied in fault detecting (Liu et al., 2018a) and time series predicting (Shahzad et al., 2017). Particularly, the VMD-based neural networks has achieved higher prediction accuracy compared with EMD-based and single neural network model in the prediction applications, such as non-ferrous metal price (Liu et al., 2020), stock price (Bisoi et al., 2019) and wind speed (Liu et al., 2018b).

However, most deep-learning-based methods utilised do not take the robustness of the prediction as optimising goals. Specifically, researches pay more attention to foreign stock markets while stock markets in developing countries (e.g., Shenzhen stock index). Therefore, the results are not significant enough. In this work, we developed a hybrid global stock closing price daily forecasting model in order to select the stock with the highest expected revenue according to the stock closing price, and capturing the daily fluctuation trends of global stock closing price in both China market and foreign market stocks.

3 Methodology

3.1 GRU architecture

LSTM and GRU model retain important states through gate functions in different ways, avoiding being lost during long-term propagation. In addition, GRU contains less parameters than LSTM, so which have faster training speed compared with LSTM. The structure of the GRU model can be formulated as follows:

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

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1}\right) \tag{2}$$

$$\tilde{h}_t = \tanh\left(U_h x_t + \left(r_t \odot h_{t-1}\right) W_h\right) \tag{3}$$

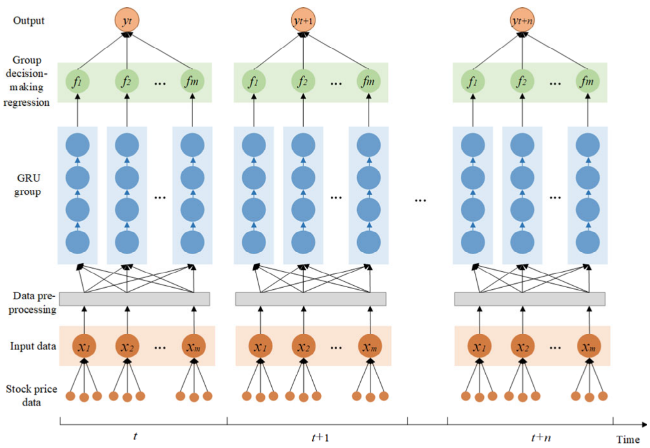
$$h_t = \left(1 - z_t\right) \odot \tilde{h}_t + z_t \odot h_{t-1} \tag{4}$$

where x_t, h_t, z_t and r_t denote input signals, output features, update gate features, and reset gate signals, respectively. W and U represent forward matrices, recurrent matrices, and biases, respectively.

3.2 The GRU_G model

The stock index prediction model, which consists of a single GRU module, may be affected by the random initialisation parameters and specific datasets, resulting in the model always achieve poor prediction results and ultimately influence the overall performance of this model. To improve the prediction accuracy and model robustness, a joint decision stock index prediction model based on GRU group is further proposed. Based on its excellent ability, the joint decision-making method based on swarm intelligence strategies can avoid the possible prediction errors of a single GRU, and then enhance the overall prediction accuracy and model robustness. In view of the advantages of GRU and swarm intelligence strategies, one constructs a hybrid framework named GRU_G fusing these two techniques. The architecture of this framework is depicted in Figure 1, in which GRU_G with group decision-making strategy operation is also shown.

Figure 1 Structure diagram of GRU group joint decision model (see online version for colours)



As shown in Figure 1, the model is composed of two parts, the first part is the GRU group, and the second part is the joint decision regression layer. First, the GRU group is composed of GRU models initialised by random parameters. They are trained and tested on the same dataset. It is assumed that the predicted results of these models are f_1, f_2, and f_m respectively. The second part is the joint decision regression layer, whose function is to make joint decision according to the prediction results of GRU group and get final prediction results. In this study, three joint decision strategies are adopted, namely balanced joint decision strategy, full connection layer joint decision strategy and filtering joint decision strategy. As a result, these three kinds of GRU group-based decision-making model can be called as balanced GRU group-based decision-making (BaGRU_G) model, the fully-connected GRU group-based decision-making (FcGRU_G) model and the filtering GRU group-based decision-making (FiGRU_G) model.

In the BaGRU_G model, each GRU model in the GRU group is treated equally. The average value of each GRU model's output is taken as the prediction result of the joint decision-making. This strategy is expressed as follows:

$$y = \frac{f_1 + f_2 + \ldots + f_m}{m} \tag{5}$$

Under the influence of parameter initialisation, the performance of each GRU module may also be different. Therefore, when training the GRU group, a fully connected joint decision layer can be trained together to learn the importance of the results of each model. That is, the weight of the GRU model with good performance is slightly larger, and that of the GRU model with poor performance is slightly smaller. Finally, the joint decision regression result can be output through the fully connected layer. This strategy can be expressed as follows:

$$y = W\left[f_1, f_2, \ldots, f_m\right] + b \tag{6}$$

where W and b are the weights and biases of joint decision regressors.

The above two joint decision models are optimised from the perspective of model. However, this FiGRU_G model is proposed directly from the angle of data. It takes targeted joint decisions based on the regression results of each data. In the FiGRU_G model, these bad joint prediction results will be eliminated, and then the remaining regression results will be averaged to get the final joint decision results. Prediction process of this FiGRU_G model is shown as follows:

Step 1 The average prediction estimate $\bar{f}$ was calculated based on the prediction results $f_1, f_2, \ldots, f_n$ of the GRU group.

Step 2 Calculate the absolute offset percentage for the predicted results of each GRU model. The calculation formula is as follows:

$$s = \frac{\left|f - \bar{f}\right|}{\bar{f}} \tag{7}$$

Step 3 Set the filtering threshold c.

Step 4 The mean value of all the filtered prediction results is calculated to get the final joint decision result.

4 Data

This study selects 29 stocks covering the China market, American market, European market and Asia-Pacific market. The data is collected from the live stock price database. These stock price indexes are collected from January 2002 to December 2019, which contain opening price, highest price, lowest price, volume, closing price and turnover. A list of above mentioned 29 global stock indexes is shown in Table 1.

Table 1 A list of 29 global stock indexes

Stock market	*Stock name*
China market	Shanghai securities composite index: Shanghai A-Shares, Shanghai B-Shares, SSE 50, SSE 180, and SSE 380. Shenzhen stock market: Shenzhen composite A share index and Shenzhen composite B share index. China securities index: CSI 300 Index, CSI 100 Index, CSI 500 Index, CSI 800 Index, and CSI 1000 Index. SSE SME composite: SZSE SME price index, SZSME, and SZSME300.
American market	Dow-Jones Index, S&P 500 Index, S&P 500 Index, S&P Pan Asia, and NASDAQ 100 Index.
European market	German DAX index, Financial Times Stock Exchange 100 Index, Cotation Assistée en Continu 40, Eurex 100, and STOXX.
Asia-Pacific market	NIKKEI 225, Korea Composite Stock Price Index, FTSE Singapore STI, and ASX 200.

Each input data is normalised to the range of [0, 1], following the standardised principles as formulated in equation (4)

$$x' = \frac{x - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

where x' indicates the standardised value of input, x denotes the original value of input, $X_{\max}$ represents the maximum value of the input while $X_{\min}$ denotes the minimum value of the input.

5 Experiments

5.1 Training of model

All the experiments in this study are implemented in Tensorflow v.1.2 on the platform of Ubuntu 16.04.

With regard to the length of the time window M, fit is the interval started from the M^{st} day backward from today for training data and from the $(M + 1)^{st}$ day to today for testing data respectively. The time length of the predicted stock price index for each time stamp can be denoted as K. More special, when the value of K equals 20, 60 and 250, it corresponds to short-term, medium-term and long-term prediction scenarios, respectively. To verify the superiority of this proposed FiGRU_G model, six competing models are used, which are the single models MLP, CNN, LSTM and GRU, and the hybrid models BaGRU_G and FcGRU_G. In the MLP model, the number of hidden units are set to 100. In this CNN model, each convolutional layer contains ten convolutional filters with kernel size 1, and kernel size of the max-pooling layer is 3. For the LSTM and GRU model, the numbers of cells are 128. These models are trained for 400 epochs with batch size 64. For these hybrid models, each method consists of three GRU model with corresponding group-based decision-making strategy. It is found that the FiGRU_U model achieves the best performance when the value of c equals 0.5.

Table 2 Summary of MAPE values of each comparison model (M = 20, 60 and 250)

	M = 20		*M = 60*		*M = 250*	
	China market	*Foreign market*	*China market*	*Foreign market*	*China market*	*Foreign market*
MLP	2.22	1.71	2.36	1.94	4.48	2.29
CNN	2.16	1.72	2.32	1.96	4.00	2.24
LSTM	1.91	1.76	2.11	1.73	3.67	1.94
GRU	1.70	1.66	1.77	1.57	3.47	1.61
BaGRU_G	1.59	1.49	1.72	1.33	3.33	1.49
FcGRU_G	1.56	1.48	1.65	1.33	3.17	1.47
FiGRU_G	*1.50*	*1.43*	*1.61*	*1.30*	*3.16*	*1.40*

Table 3 Summary of SDAPE values of each comparison model (M = 20, 60 and 250)

	M = 20		*M = 60*		*M = 250*	
	China market	*Foreign market*	*China market*	*Foreign market*	*China market*	*Foreign market*
MLP	2.20	1.69	2.33	1.92	4.44	2.27
CNN	2.14	1.70	2.29	1.94	3.96	2.21
LSTM	1.89	1.74	2.09	1.72	3.63	1.92
GRU	1.68	1.64	1.75	1.55	3.44	1.60
BaGRU_G	1.58	1.47	1.72	1.32	3.30	1.47
FcGRU_G	1.54	1.46	1.63	1.31	3.14	1.45
FiGRU_G	*1.49*	*1.42*	*1.60*	*1.28*	*3.13*	*1.38*

5.2 Evaluation criteria

The commonly used mean absolute percentage error (MAPE) and standard deviation average percentage error (SDAPE) are used as evaluate metrics of prediction accuracy, which can be respectively formulated as:

$$MAPE = \frac{1}{N} \times \sum\nolimits_{i=1}^{N} \left| \frac{T_i - A_i}{A_i} \right| \times 100\% \tag{9}$$

$$SDAPE = \sqrt{\frac{1}{N} \sum\nolimits_{i=1}^{N} \left(\left| \frac{T_i - A_i}{A_i} \right| - MAPE \right)^2} \tag{10}$$

where T_i denotes the predictive value, A_i represents the actual value, and N is the number of sample points of the predictive results. MAPE can represent the accuracy of the prediction. The smaller the MAPE is, the more accurate the prediction is. MAPE can calculate the average relative errors between prediction results and the ground truth. The smaller the MAPE value is, the less different they are, which also indicates the higher prediction accuracy. SDAPE reflect the stability of prediction. Generally, the smaller the SDAPE is, the better the stability is.

5.3 Performance evaluation

Comparing the effects of prediction when the values of time window M taking 20, 40, 60, 90 and 250, then the best performance can be achieved when M equals 60. Table 2 demonstrates the forecasting 198 results of the selected stocks in the test dataset compared to other models when K takes different values. To facilitate observation, only the mean values of the evaluation indices are represented.

As shown in Table 2, the final values of MAPE for each market are computed by averaging the values of all the selected stocks. When the values of time window M take 20, 60 and 250, they correspond to short-term, medium-term and long-term input scenarios respectively. It is shown visually that the FiGRU_G model achieves the best prediction accuracy in the short-term prediction scenario. What is more, the predicted results of this proposed FiGRU_G model has generally smaller relative errors, indicating the best MAPE in China market and Foreign market stocks. Table 3 also presents the average values of the SDAPE for all the China market stocks and foreign market stocks in these different scenarios.

In Table 3, the FiGRU_G framework can obtain the best stability in the three scenarios, i.e., short-term prediction, middle-term prediction and long-term prediction. In the short-term forecast, the SDAPE value obtained in the China stock market of FiGRU_G is 1.68, which is 19% higher than the result of the single GRU model. In the long-term forecast, the SDAPE value obtained in the FiGRU_G for foreign stock market is 1.38, which is 22% higher than the result of the single GRU model.

Table 4 quantitatively display detailed comparisons of the MAPE and SDAPE for all the 15 China stocks in short-term prediction scenario among different models, i.e., GRU, BaGRU_G, BaGRU_G and BaGRU_G.

Table 4 Forecasting results of the stock closing price on the Chinese market in short-term input scenario

Stocks \ *Criteria*	*GRU*		*BaGRU_G*		*FcGRU_G*		*FiGRU_G*	
	MAPE	*SDAPE*	*MAPE*	*SDAPE*	*MAPE*	*SDAPE*	*MAPE*	*SDAPE*
Shanghai A-Shares	1.16	1.15	1.51	1.50	1.16	1.15	*0.98*	*0.97*
Shanghai B-Shares	2.33	2.31	2.21	2.19	*2.19*	*2.17*	2.26	2.24
SSE 50	1.29	1.28	1.30	1.29	1.37	1.36	*1.28*	*1.27*
SSE 180	1.13	1.12	*1.04*	*1.03*	1.20	1.19	1.11	1.10
SSE 380	2.15	2.13	1.41	1.40	*1.33*	*1.32*	1.58	1.56
Shenzhen A-share composite	1.69	1.67	1.41	1.40	1.62	1.60	*1.34*	*1.33*
Shenzhen B-share composite	0.97	0.96	0.98	0.97	1.36	1.34	*0.87*	*0.86*
CSI 100 Index	1.20	1.19	*1.15*	*1.14*	1.21	1.20	1.19	1.18
CSI 300 Index	1.31	1.30	1.15	1.14	*1.13*	*1.12*	1.18	1.17
CSI 500 Index	1.41	1.40	1.23	1.22	*1.20*	*1.19*	1.22	1.21
CSI 800 Index	1.39	1.37	1.11	1.09	*1.10*	*1.09*	1.17	1.16
CSI 1000 Index	2.75	2.72	2.21	2.19	2.23	2.21	*2.10*	*2.08*
SZSE SME price index SZSME300	1.71	1.69	1.75	1.73	1.71	1.69	*1.70*	*1.68*
SZSME	*1.45*	*1.43*	1.82	1.80	1.48	1.47	1.47	1.46
SZSME300	3.52	3.48	3.64	3.61	3.10	3.07	*3.09*	*3.06*
Mean value	1.70	1.68	1.59	1.58	1.56	1.54	*1.50*	*1.49*

Table 5 Forecasting results of the stock closing price on the international market in short-term input scenario

Stocks \ *Criteria*	*GRU*		*BaGRU_G*		*FcGRU_G*		*FiGRU_G*	
	MAPE	*SDAPE*	*MAPE*	*SDAPE*	*MAPE*	*SDAPE*	*MAPE*	*SDAPE*
S&P 100 Index	2.55	2.52	2.85	2.82	2.69	2.67	*2.48*	*2.46*
Dow-Jones Index	1.72	1.70	*1.12*	*1.11*	1.27	1.26	1.39	1.38
S&P Pan Asia	1.13	1.12	1.09	1.08	*1.08*	*1.07*	1.10	1.09
S&P 500 Index	1.58	1.56	*1.30*	*1.29*	1.78	1.76	1.42	1.41
NASDAQ 100 Index	2.18	2.16	*1.33*	*1.31*	1.40	1.38	1.57	1.56
German DAX Index	1.01	1.00	*0.83*	*0.82*	1.15	1.14	1.02	1.01
Financial Times Stock Exchange 100 Index	2.03	2.00	*1.62*	*1.60*	1.78	1.76	1.76	1.74
Cotation Assistée en Continu 40	1.59	1.58	1.11	1.10	1.29	1.28	*1.07*	*1.06*
Eurex 100	2.81	2.78	2.51	2.48	*2.39*	*2.37*	2.45	2.42
STOXX	0.91	0.90	0.93	0.91	*0.87*	*0.86*	0.96	0.95
NIKKEI 225	0.92	0.91	1.00	0.99	1.03	1.02	*0.84*	*0.83*
Korea Composite Stock Price Index	1.51	1.50	1.33	1.32	*1.32*	*1.31*	1.45	1.44
FTSE Singapore STI	0.88	0.87	0.86	0.85	0.71	0.70	*0.62*	*0.61*
ASX 200	2.35	2.32	2.07	2.05	1.90	1.88	*1.87*	*1.85*
Mean value	1.66	1.64	1.49	1.47	1.48	1.46	*1.43*	*1.42*

In Table 4, the best values of MAPE and SDAPE for each stock are represented in bold. Among the 15 Chinese stocks, the numbers of stocks that GRU, BaGRU_G, FcGRU_G and FiGRU_G algorithms can obtain the best prediction values are 1, 2, 5 and 7, respectively. For the Chinese stock market, this proposed FiGRU_G model gets the best performance with 1.50 in mean value of MAPE and 1.49 in mean value of SDAPE. GRU model achieves the worst performance, which indicates that only using single GRU model cannot capture the coupling effects. In addition, Table 5 shows the prediction performance of the daily stock price index for the 14 international stocks in short-term prediction scenario.

As shown in Table 5, the FiGRU_G model can also realise the best performance in predicting international stock market. In general, the prediction results of GRU model and GRU group-based decision-making model are relatively smooth, and the prediction performance of each stock is relatively consistent. Obviously, GRU group-based decision-making model is superior to single GRU model in both prediction accuracy and stability. It proves that GRU group-based decision-making model can supplement each other through multiple models to make up for the prediction error of single model and improve the prediction effect.

Comparing the predicted results of these three kinds of GRU group-based decision-making model, the FiGRU_G model always shows the best performance, the FcGRU_G framework is better than the BaGRU_G framework and worse that the FiGRU_G framework. The main reason is that FcGRU_G model adds model weight on the basis of BaGRU_G model, indicating the model correlation information is of great importance. While FiGRU_G model optimises predicted correction based on each data.

When analyzing the results of the short-term prediction scenario for the stock price index in the Chinese market, the FiGRU_G framework achieves 20% and 19% performance improvement on indices MAPE and SDAPE respectively compared with the GRU model. In the short-term prediction scenario prediction results in international markets, the FiGRU_G model achieves 23% and 22% performance improvement on evaluation criteria MAPE and SDAPE respectively compared to the GRU model. In general, it demonstrates that the FiGRU_G model has stronger adaptability and is the optimal model.

In general, the results of GRU model and GRU group-based decision-making model are relatively smooth, and the prediction performance of each stock is relatively consistent. Obviously, GRU group-based decision-making model is superior to single GRU model in both prediction accuracy and stability. It proves that GRU group-based decision-making model can supplement each other through multiple models to make up for the prediction error of single model and improve the effect.

6 Conclusions and future work

In this research, a hybrid neural network FiGRU_G framework is proposed to predict stock closing prices with nonlinearity, non-stationarity and uncertainty. MAPE and SDAPE are utilised to evaluate the accuracies and robustness. After comparison with four single models, i.e., MLP, CNN, LSTM, GRU, and two hybrid models, i.e., the BaGRU_G and FcGRU_G, this proposed FiGRU_G model represents the best performance.

This work needs to be further advanced, including incorporating other data sources such as knowledge graph to enhance the prediction judgement.

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