Mixed modified fruit fly optimization algorithm with general regression neural network to build oil and gold prices forecasting model

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Abstract

Purpose – When facing a clouded global economy, many countries would increase their gold reserves. On the other hand, oil supply and demand depends on the political and economic situations of oil producing countries and their production technologies. Both oil and gold reserve play important roles in the economic development of a country. The paper aims to discuss this issue.

Design/methodology/approach – This paper uses the historical data of oil and gold prices as research data, and uses the historical price tendency charts of oil and gold, as well as cluster analysis, to discuss the correlation between the historical data of oil and gold prices. By referring to the technical index equation of stocks, the technical indices of oil and gold prices are calculated as the independent variable and the closing price as the dependent variable of the forecasting model.

Findings – The findings indicate that there is no obvious correlation between the price tendencies of oil and gold. According to five evaluating indicators, the MFOAGRNN forecast model has better forecast ability than the other three forecasting models.

Originality/value – This paper explored the correlation between oil and gold prices, and built oil and gold prices forecasting models. In addition, this paper proposes a modified FOA (MFOA), where an escape parameter Δ is added to Si. The findings showed that the forecasting model that combines MFOA and GRNN has the best ability to forecast the closing price of oil and gold.

Keywords Information technology, Algorithms, Optimization techniques, Economics, Modelling, Artificial intelligence

Paper type Research paper

Introduction

Evolutionary Computation is a common noun that refers to "the survival of the fittest and the elimination of the unfit" of the Darwinian Theory. This concept simulates the algorithm established by the nature in the course of evolution, such as the Artificial Fish Swarm Algorithm proposed by Li *et al.* (2002). This algorithm was developed from the foraging behaviors of animal populations, thus, they are called swarm intelligence algorithms by some scholars. However, as both algorithms need to search for the optimal solution through iterative search, they belong to the Evolutionary Computation. Organisms rely on their instincts to survive, which are the research focusses of many scholars. This paper uses the historical data of oil and gold prices as research data, and uses the historical price tendency charts of oil and gold, as well as cluster analysis, to discuss the correlation between the historical data of oil and gold prices. By referring to the technical index equation of stocks, the technical indices of oil

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and gold prices are calculated as the independent variable (X) and the closing price as the dependent variable (Y) of the forecasting model. This model uses a relatively new Evolutionary Computation technique, called the Fruit Fly Optimization Algorithm (FOA), which theory is modified to form the Modified Fruit Fly Optimization Algorithm (MFOA). This algorithm is used to optimize the General Regression Neural Network (GRNN) parameters to build the oil and gold prices forecasting (MFOAGRNN) model, for comparison with the FOA optimized GRNN (FOAGRNN) model, GRNN model, and Multiple Regression (MR) model for forecasting ability. The findings can serve as references for future studies.

This paper is organized as follows: first section introduces the research purposes; second section describes FOA, MFOA, and literature review; third section discusses the sample data and empirical analysis; fourth section gives conclusions and suggestions.

FOA and MFOA

As the GRNN is a simple and common neural network model, it is not introduced herein. This section only describes the FOA and MFOA.

FOA

The FOA was proposed by Pan (2012), and a number of studies have cited this algorithm (Li *et al.*, 2012a, b; Yang *et al.*, 2012; Abidin *et al.*, 2012; Cheng and Liu, 2013). It is a new method for deducing global optimization based on the foraging behavior of fruit flies. The sensory perception of fruit flies is better than that of other species, especially the sense of smell and vision. The olfactory organ of a fruit fly can gather various smells from the air, and even a food source 40 km away. The fruit fly flies toward the food, uses its acute vision to find the food and the location where other fruit flies. The fly paths are as shown in Figure 1.

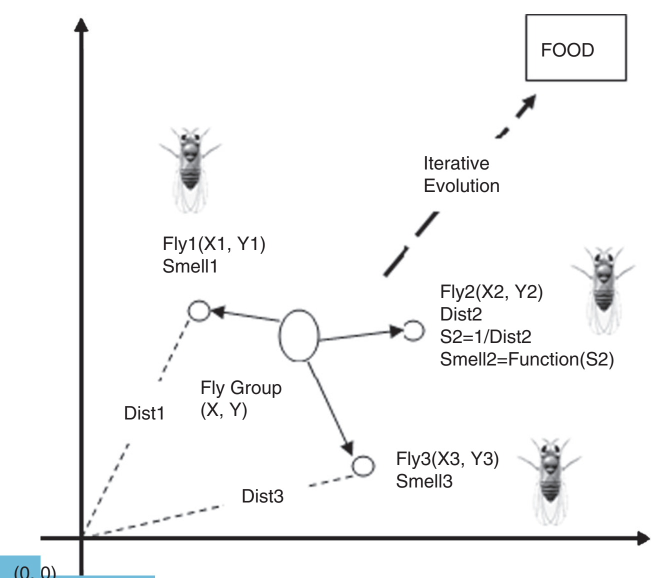

Figure 1.
Schematic diagram of iterative search for food of fruit fly swarm

The foraging behaviors of fruit flies are summarized into the following steps:

- The random initial position of a fruit fly swarm is as shown in the right of Figure 1:

$$\text{InitX\_axis; InitY\_axis} \tag{1}$$

- The random foraging direction and distance of a fruit fly, by using the sense of smell, is:

$$\begin{aligned} X_i &= X\_axis + \text{Random Value} \\ Y_i &= Y\_axis + \text{Random Value} \end{aligned} \tag{2}$$

- As the location of food is unknown, the distance (Dist) to the origin is estimated before the decision value of smell concentration (S) is calculated; this value is the reciprocal of distance:

$$\text{Dist}_i = \sqrt{X_j^2 + Y_j^2}; S_i = \frac{1}{\text{Dist}_i} \tag{3}$$

- The smell concentration decision value (S) is substituted in the smell concentration decision function (the Fitness function) to obtain the smell concentration (Smelli) in the position of the individual fruit fly:

$$\text{Smell}_i = \text{Function}(S_i) \tag{4}$$

- Determine the fruit fly with the maximum smell concentration among the fruit fly swarm (calculate the maximum value):

$$[\textit{bestSmell bestIndex}] = \textit{max}(\textit{Smell}) \tag{5}$$

- Retain the best smell concentration value and x, y coordinates, here the fruit fly swarm flies toward the position by vision:

$$\begin{aligned} \text{Smellbest} &= \text{bestSmell} \\ X\_axis &= X(\text{bestIndex}) \\ Y\_axis &= Y(\text{bestIndex}) \end{aligned} \tag{6}$$

Enter into iterative optimization, repeat Steps 2-5, and determine whether the smell concentration is better than the previous iterative smell concentration, if yes, go to Step 6.

Modified FOA
A discussion on the forum of the Matlab web site of China (www.ilovematlab.cn/forum.php?mod=viewthread&tid=145979) has suggested that the FOA is likely to remain in the local extremum, and the global extremum cannot be found, which is resulted from the fitness function for FOA. In order to escape from local extremum, the fitness function must be corrected, namely, S_i must be corrected. In addition, distance Dist_i is positive, S_i is also positive as the reciprocal of distance; therefore, the fitness function of FOA cannot be negative. This is the problem indicated by a number of scholars. This paper proposes a modified FOA (MFOA), where an escape parameter Δ is added to S_i. By using this parameter, the global extremum can be determined by escaping the local minimum,

and the fitness function can be negative. The modified S_i is expressed as the following equation:

$$S_i = \frac{I}{Dist_i} + \Delta; \Delta = Dist_i \times (0.5 - \delta); 0 \leqq \delta \leqq 1 \tag{7}$$

In addition, the fruit fly flies in three-dimensional space, while the original FOA searches for the global extremum in two-dimensional space, thus, the optimal value in three-dimensional space may not be searched. Therefore, this paper modifies the first three steps of the FOA procedures into:

- The random initial position of fruit fly swarm is shown in the right of Figure 1:

$$\text{InitX\_axis; InitY\_axis; InitZ\_axis} \tag{8}$$

- The random foraging direction and distance of a fruit fly, by using sense of smell, is:

$$\begin{aligned} X_i &= \text{X\_axis} + \text{Random Value} \\ Y_i &= \text{Y\_axis} + \text{Random Value} \\ Z_i &= \text{Z\_axis} + \text{Random Value} \end{aligned} \tag{9}$$

- As the location of food is unknown, the distance (Dist) to the origin is estimated before the decision value of smell concentration (S) is calculated; this value is the reciprocal of distance:

$$Dist_i = \sqrt{X_j^2 + Y_j^2 + Z_j^2}; S_i = \frac{I}{Dist_i} + \Delta \tag{10}$$

Empirical research

Sample data and variables

The historical data of West Texas Intermediate (WTI) crude oil price and gold transactions in Taiwan were sourced from domestic and foreign databases. More than 1,500 pieces of daily transaction data were collected between January 2007 and December 2012. The historical tendencies are as shown in Figure 2.

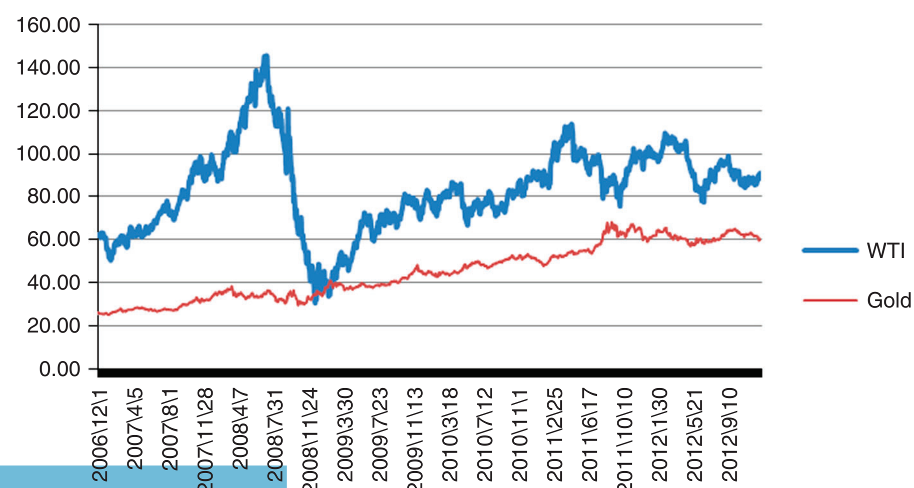

Figure 2.
Tendency chart of closing prices of oil and gold

Oil price is likely to be influenced by the policies of oil producing countries and the international economic situation, while gold is an inflation-proof instrument in a clouded global economy, and is an investment and financing instrument when the global economy is sound. Therefore, some financial and economic experts believe that the oil and gold price tendencies are correlated. In order to clarify the tendencies of oil and gold prices, this paper first divides the gold price by 100. In the above figure, due to the financial tsunami in 2008, the WTI oil price dropped from a high price of US$150 per barrel to US$40, while the fluctuation range of gold prices continuously increases in this interval. Later, the oil price rises upward, while gold price steadily increase, until the beginning of 2011, when the international oil price fluctuates again. Although the slowdown of global economic growth clouds crude oil demand, and the tense situation in some Middle East countries raises the oil price to US$100 per barrel, gold prices continue to increase. As the economic growths of the US, Europe, and emerging economies face different resistances, under unstable demand for oil, both oil and gold prices fluctuate. Therefore, it is difficult to identify the correlation in the figure. Fuzzy C-means clustering (Bezdek, 1981) and Fuzzy Sammon Mapping algorithm (Kov'acs and Abonyi, 2002) are used to analyze the relationship between oil and gold prices. The analytic results are as shown in Figure 3.

The data are divided into three clusters by Fuzzy C-means clustering, and the data distribution in a highly dimensional space is reduced to a two-dimensional space by the Fuzzy Sammon Mapping algorithm. As shown in the figure, two clusters of the majority have a positive correlation, and according to the data series and tendency chart, a cluster has a highly positive correlation. The data of this cluster centers between December 2006 and March 2008, February 2009 and April 2011. It is observed in the tendency chart that, the oil and gold prices rise at the same time. One cluster has a low positive correlation, the data of this cluster concentrate between March 2008 and November 2008, November 2011 and September 2012. It is observed in the tendency chart that, there is no obvious change in the gold price tendency when the oil price rises. Another cluster has a negative correlation, and the data volume are apparently smaller and distributed in the right lower corner of the chart. Analysis has found that, the interval of negative correlation concentrates between March 2011 and November 2011. The slowdown of global economic growth results in the drop of oil prices during this period; however, investors have a bearish estimation of the future economic

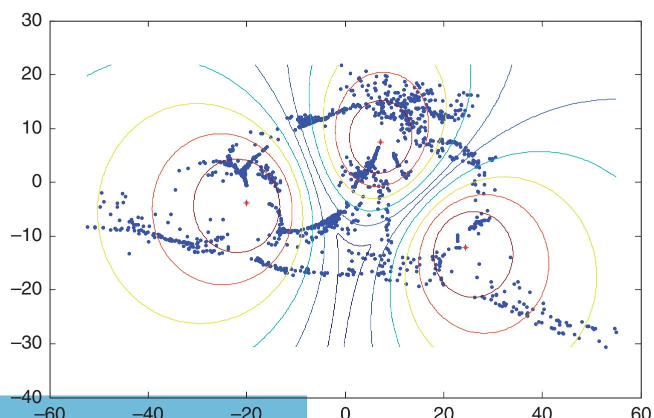

Figure 3.
Analytic result of Fuzzy C-means clustering combined with Fuzzy Sammon Mapping algorithm

condition; thus, gold becomes a popular inflation-proof and investment product, and the price is expected to rise. According to the three clusters of data, there is no obvious correlation between the gold and oil price tendencies.

In the construction of the prediction model in this paper, as the stock technical indexes have very good ability to forecast the rise and fall of stock price, so there have been lots of financial scholars (Khan *et al.*, 2010; Chavarnakul and Enke, 2008) adopting stock technical indexes to conduct stock prediction modeling so far. As technical indexes cover the tendency and characteristics of study objects (including stock, fund, petroleum and gold), so it is very suitable to take it as the predictive index variable for oil or gold prediction. Differing from previous scholars (Baker and Van-Tassel, 1985; Abdullah and Zeng, 2010), in this paper, the oil and gold prices are substituted into the equation of the technical index of stock. The technical indices of oil and gold prices are determined as independent variable (X), while the closing price of oil and gold is used as dependent variable (Y), which form the sample data in this paper. Therefore, this paper redefines the equations of five technical indexes of stock, as follows:

$$\text{5 days' MA} = \text{Sum of 5 days' closing prices of oil or gold}/\text{5days} \tag{11}$$

$$\begin{aligned}\text{5 days' W\%R} = {} & 100 - (\text{maximum price of oil or gold within 5 days} - \text{current} \\ & \text{closing price of oil or gold})/(\text{maximum price of oil or gold within 5 days} - \text{minimum} \\ & \text{price of oil or gold within 5 days}) \times 100\end{aligned} \tag{12}$$

$$\begin{aligned}\text{5 days' BIAS} = {} & (\text{current closing price of oil or gold} - \text{5 days' average closing price} \\ & \text{of oil or gold})/\text{5 days' average closing ' of oil or gold} \times 100\end{aligned} \tag{13}$$

$$\text{Current K value} = 2/3\,\text{last day's K value} + 1/3\,\text{RSV} \tag{14}$$

$$\text{Current D value} = 2/3\,\text{last day's D value} + 1/3\,\text{current K value} \tag{15}$$

$$\begin{aligned}\text{where 5 days' RSV} = {} & (\text{current closing price of oil or gold} - \text{minimum price of oil or} \\ & \text{gold within 5 days})/(\text{maximum price of oil or gold within 5 days} - \text{minimum price} \\ & \text{of oil or gold within 5 days}) \times 100\end{aligned} \tag{16}$$

When the technical indices for calculating oil and gold prices are completed, this paper extracts 1,500 sample data to build the oil and gold prices forecasting models. Table I show the technical indices of oil and gold prices, which are divided into five groups. Group 1 uses No. 1 to 1,000 data as model training data, and No. 1,001 to 1,100 data as model testing data; Group 2 uses No. 101 to 1,100 data as model training data, and No. 1,101 to 1,200 data as model testing data; Group 3 uses No. 201 to 1,200 data as model training data, and No. 1,201 to 1,300 data as model testing data; Group 4 uses No. 301 to 1,300 data as model training data, and No. 1,301 to 1,400 data as model testing data; Group 5 uses No. 401 to 1,400 data as model training data, and No. 1401 to 1,500 data as model testing data; Group 1 has 1,000 training data and 100 testing data. Therefore, the final model prediction results have 500 data for analyzing the forecast abilities of the varied models.

Constructing four oil and gold closing prices forecasting models

The smoothing parameter Spread value of GRNN can influence the forecasting ability of GRNN, and the default of Spread prevents GRNN from having accurate forecast ability, thus, it must be adjusted. This paper uses FOA and MFOA, respectively, to adjust the Spread value of GRNN.

In the setup of the initial parameters of FOA and MFOA, the fruit fly swarm's position interval is randomly initialized to [0, 1], the flying direction and distance interval of the iterative fruit flies is set to [−10, 10], the population of the fruit fly swarm is 20, and the iteration times is 100. To optimize GRNN with FOA and MFOA, the distance between the position of each fly and the point of origin (0, 0, 0) is calculated, and then inversed to obtain the judged value of smell concentration, which is then substituted into the spread parameter of GRNN. After that, training data are input to obtain network output, which is used in conjunction with the target value to calculate RMSE (the Fitness). A smaller RMSE indicates a better fit. Finally, the judged value of best smell concentration (S) is taken as the spread value of GRNN, and iterative search is conducted with the same method. The spread parameter of GRNN can be adjusted to the best value by simulating the random foraging behavior of fruit flies, which would gather at the location where the smell concentration is the best. Thus, the RMSE between network output and target value can be adjusted to the minimum. In terms of the GRNN model, Spread parameter default (1) is used to build the oil and gold prices forecasting models, which are compared with the MR Model for the forecasting ability.

Figure 4 shows the flight routes of the fruit fly swarms of FOA and MFOA forecasting models, as built by the training data of Group 1 for oil and gold prices. It is found that the flight route of the fruit fly swarm of MFOA is shorter, largely fluctuates, and converges faster, after 100 times of iterative evolutions. The data of the Group 1 oil price forecasting model begin to converge in the 16th generation, at coordinates (57.2140, 39.2166, 82.1267), with a Spread value of 0.0035, and program execution time of 450.696873 seconds. The data of Group 1 of gold price forecasting model begin to converge in the 14th generation, at coordinates (−121.5105, 53.5503, 20.7745), with a Spread value of 0.0074, and program execution time of 359.367819 seconds.

The flight route of fruit fly swarm of FOA is longer, fluctuates slightly, and converges slowly, after 100 times of iterative evolution. The data of Group 1 of the oil price forecasting model begin to converge in the 67th generation, at coordinates (438.7025, −203.2127), with a Spread value of 0.0021, and program execution time of 6541.484843 seconds. The data of Group 1 of gold price forecasting model begin to converge in the 97th generation, at coordinates (475.0887, 420.7827), with a Spread value of 0.0016, and program execution time of 9660.012920 seconds.

Item	Index	X1	X2	X3	X4	X5
Oil	Max	18.4029	1.0100	1.4224	0.3667	0.3654
	Min	−16.5312	0.0100	0.3267	0.0333	0.0369
	Avg	0.0754	0.4731	0.8426	0.2123	0.2122
	Std	2.8337	0.4241	0.1988	0.1414	0.0926
Gold	Max	25.1314	1.0001	6.6893	0.3667	0.3654
	Min	−99.8533	0.0001	3.0833	0.0333	0.0400
	Avg	0.0745	0.4487	4.8329	0.2171	0.2174
	Std	3.0839	0.4183	1.0713	0.1394	0.0894

Table I. Descriptive statistics of technical indexes of oil and gold prices

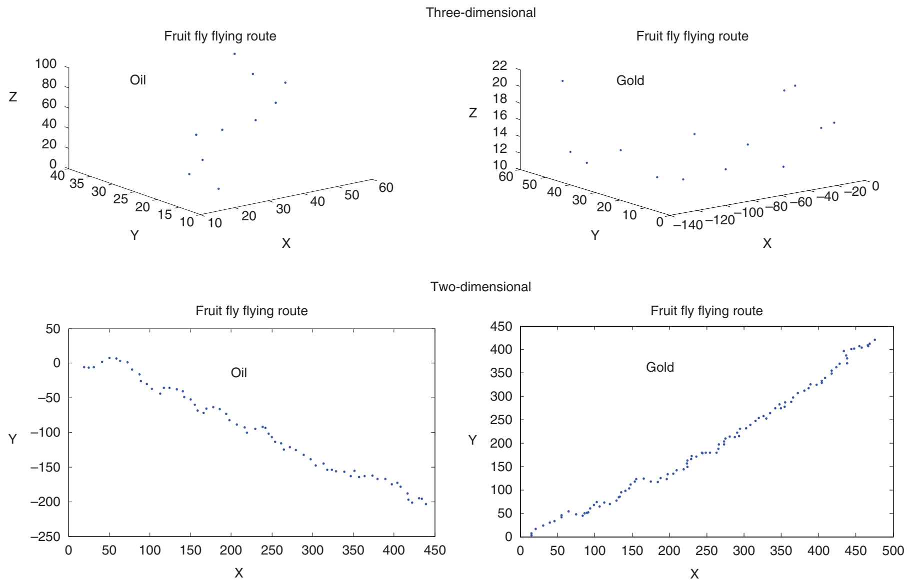

Figure 4.
Flight routes of fruit fly swarm of data of Group 1 used in Fruit Fly Optimization Algorithm and Modified Fruit Fly Optimization Algorithm

Comprehensive comparison of forecast ability of four models

The testing data of the five groups are imported into four oil and gold prices forecasting models for prediction, in order to test the stability of these forecasting models. Figures 5 and 6 show the sample point clustering trend in the prediction results of four oil and gold prices forecasting models, where the closer the sample points are to the 45° line, the closer the forecast value to the target value, and the better the forecast ability of the model. As seen, for both oil and gold prices forecasting models, the MFOAGRNN model has the best forecast ability.

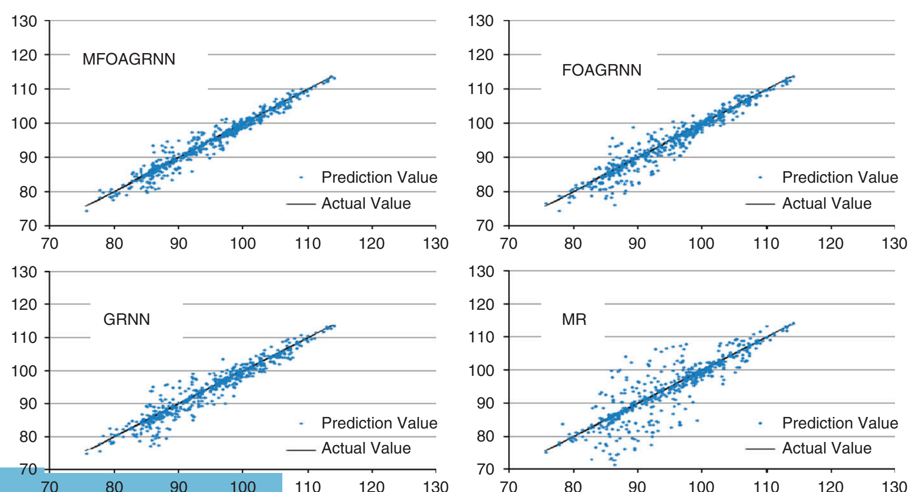

Figure 5.
Sample point clustering trend in prediction results of four oil price forecasting models

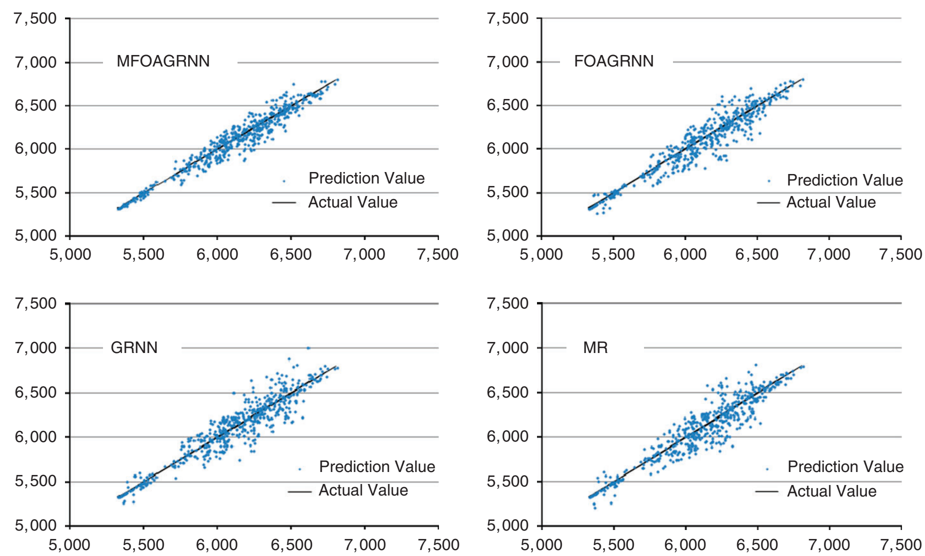

Figure 6.
Sample point clustering trend in prediction results of four gold price forecasting models

This paper also uses five evaluating indicators to compare the forecast abilities of the four models, which are:

(1) Root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\sum_{t=1}^{n} \left(X_t - \widehat{X}_t\right)^2 / n} \tag{17}$$

RMSE is an absolute error measure that squares the deviations to keep the positive and negative deviations from canceling one another out.

(2) Revision theil inequality coefficient (RTIC):

$$\mathrm{RTIC} = \sqrt{\frac{\sum_{t=1}^{n} \left(X_t - \widehat{X}_t\right)^2}{\sum_{t=1}^{n} (X_t)^2}} \tag{18}$$

is a measure of the degree of difference between two sequences.

(3) Mean absolute error (MAE):

$$\mathrm{MAE} = \frac{1}{n} \sum_{t=1}^{n} \left|X_t - \widehat{X}_t\right| \tag{19}$$

where n is the number of predicted values, X_t is the time of observation, $(\widehat{X}_t)$ is the estimated time of Value.

(4) Mean absolute percentage error:

$$\mathrm{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left|\frac{X_t - \widehat{X}_t}{X_t}\right| \tag{20}$$

mean absolute percentage error is an accuracy measure based on percentage (or relative) errors.

(5) Coefficient of determination:

$$\mathrm{CE} = 1 - \frac{\sum_{t=1}^{n}\left(X_t - \widehat{X}_t\right)^2}{\sum_{t=1}^{n}\left(X_t - \overline{X}_t\right)^2} \tag{21}$$

Indicates how well data points fit a statistical model.

Among the five evaluating indicators, the closer the indicators 1 through 4 are to 0, the more accurate the model. The closer the fifth indicator is to 1, the more accurate the model. The analytic results of the testing data are as shown in Table II.

According to Table II, among the five evaluating indicators of the MFOAGRNN forecasting model for oil price, RMSE is 1.155, RTIC is 0.015, MAE is 0.994, and MAPE is 0.010, lower than FOAGRNN, GRNN and MR; and CE is 0.966, also higher than the other three models. Among the five evaluating indicators of MFOAGRNN forecasting model for gold price, RMSE is 71.400, RTIC is 0.015, MAE is 53.422, and MAPE is 0.008, lower than FOAGRNN, GRNN and MR; and CE is 0.950, higher than the other three models. Therefore, the MFOAGRNN forecasting model has better forecast ability than the other three models.

Conclusions and suggestions

This paper explored the correlation between oil and gold prices, and built oil and gold prices forecasting models. There are numerous factors influencing the oil and gold prices, the closing prices of oil and gold are highly random; therefore, the oil and gold prices forecasting models should be as accurate as possible. The findings of the tendency chart and cluster analysis indicate that there is no significant correlation between oil and gold prices. In addition, this study built four oil and gold prices forecasting models to forecast the closing prices of oil and gold. The findings showed that the forecasting model that combines MFOA and GRNN has the best ability to forecast the closing price of oil and gold.

In addition, this paper used FOA and MFOA to optimize the forecasting model, which can be compared with other algorithms, such as Bee Colony Optimization proposed by Professor Teodorovic *et al.* (2006), in the future.

Item	Model	RMSE	RTIC	MAE	MAPE	CE
Oil	MFOAGRNN	1.155	0.015	0.994	0.010	0.966
	FOAGRNN	1.679	0.021	1.302	0.015	0.947
	GRNN	2.450	0.026	1.643	0.018	0.905
	MR	2.730	0.053	2.352	0.032	0.874
Gold	MFOAGRNN	71.400	0.015	53.422	0.008	0.950
	FOAGRNN	95.502	0.018	77.316	0.010	0.911
	GRNN	114.331	0.020	89.033	0.013	0.896
	MR	131.982	0.022	98.243	0.016	0.849

Table II.
Evaluation results of five evaluating indicators

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