Trading Prediction Model and Strategy Formulation Based on Grey System

Fulin Li, Shuai Liu, Rusong Chen*

School of Energy and Power Engineering, Beihang University, Beijing, 102206

*Corresponding author. Email: chenrusong0407@163.com

Abstract. In this paper, we study the optimal investment strategy between gold and Bitcoin, establish a market price forecasting system using the grey forecasting model GM (1,1), and calculate the optimal investment between gold and Bitcoin through the association rule algorithm. Optimal investment ratio, and then determine the maximum return. The establishment of predictive investment models helps investors to formulate optimal investment plans. The established model can use certain data from previous years to predict the future exchange rate prices of gold and bitcoin and help trading investors make optimal buying and selling decisions. It has a certain model planning ability for investment in real life and has specific practical significance for trade investors.

Keywords: Grey prediction, GM (1, 1), association rule algorithm, incremental progress, predict investment.

1. Introduction

Market traders often buy and sell stocks to maximize their total return. There is often a return commission for each purchase and sale. Two of the best examples are gold and bitcoin. In real life, many people will continue to buy and sell gold and bitcoin, so when to buy and when to sell has become the most critical issue for traders.

The value of the cash will not change with time. It will not depreciate or increase in value: In real life, cash, the most commonly used currency, will depreciate or increase in value with inflation or deflation, so the value of cash may change with time. However, in this case, the value of gold and bitcoin is needed to measure through the value of a currency over five years. To ensure comparability, the value of cash cannot be changed. In this case, the hypothesis has a foothold.

Traders do not trade irrationally: In behavioral finance, investors are irrational. To varying degrees, any individual investor's judgment and decision-making process will be affected by cognitive, emotional, will, and other psychological factors. Investors may consider from the starting point of overconfidence, resistance to psychological analysis, and eventually produce irrational behavior bias. In order to avoid uncontrollable factors caused by irrationality, we carry out trade and investment according to the optimal solution provided by the model.

The exchange rates of gold and bitcoin do not influence each other: We conducted a 2×2 contingency table test of the exchange rates of gold and bitcoin within a certain period and found no correlation between the exchange rates of gold and bitcoin. Therefore, we assumed that there was no influence between the exchange rates of gold and bitcoin. That is, corresponding exchange rates could be predicted, respectively.

We only use the price of one year before the trading date for prediction: We found that the price of a long term has no great impact on the price fluctuation of that day and even produces greater errors. Therefore, we decided only to use one year's price for prediction, which is also of particular significance in real life.

For trade investors, when the assets they own are fixed, how to maximize the profits is our goal. The model established in this paper can predict the exchange rate prices of gold and bitcoin in the future with certain data in previous years and help trade investors make optimal buying and selling decisions. Although the model has limitations on bitcoin and gold and many assumptions, it has a certain model planning ability for investment in real life and has particular practical significance for trade investors.

2. GM(1,1) Model

Based on the gray model GM (1,1) [1], we can predict the price of financial products on the next working day and record it as the predicted value $\overline{P_{t+1}}$. For the actual price of the financial product on the next business day, write it down as the actual value P_{t+1}. Here, for the sake of measurement, we take the relative error of the new variable β_t, it is defined as the ratio between the absolute value of the difference between the predicted value and the actual value, and the calculation formula is as follows:

$$\beta_t = \frac{|\overline{P_{t+1}} - P_{t+1}|}{P_{t+1}} \times 100\% \quad (1)$$

The forecast model has higher accuracy and validity than the letter, the prediction model. It is known that the next two kinds of financial products price forecasting are based on historical data and reflect the price change rule to predict, but the price change rule and statistical data method have a very strong relationship. In order to improve the accuracy of the prediction results obtained by the constructed model, we choose to adopt the method of multi-period comprehensive prediction.
Average the predicted value of each cycle sequence can be obtained as:

$$\overline{P_{t+1}} = \frac{\sum_{i=1}^{n} P_i(t+1)}{n} \quad (2)$$

The forecast value is the predicted price of gold or bitcoin for that day. Next, we establish the association algorithm model of trading strategy demonstration.

The association rule is the logical implication relation in the form of XY, where XI, YI, and XY= φ, X is called the precursor of the rule, and Y is the result. There is support and trust for the association rule XY. In this case, X is the price of gold, and Y is the bitcoin price. Next, we will manage yellow Chicken and Bitcoin and calculate the optimal trading strategy.

A level ratio test tests the time series before the grey prediction model GM (1, 1) is established. If the sequence passes the step ratio test, it indicates that it is suitable for constructing the gray model. If it does not pass the step ratio test, the sequence is translated to make the new sequence meet the step ratio test.

The rationality of the grey prediction model can be determined only after the test, and only the model that passes the test can be used for prediction. SPSSPR mainly tests the grey prediction model through the posterior difference ratio C value, which is shown in table 1.

Table 1. Results of grade ratio test results

An index entry	The original value	The magnitude ratio	Translation translated sequence value	The ratio of the stage after translation conversion
1	35816.17	-	85764.17	-
2	37313.18	0.96	87261.18	0.983
3	38324.87	0.974	88272.87	0.989
4	31686.55	1.209	81634.55	1.081
5	32160.91	0.985	82108.91	0.994
6	33536.88	0.959	83484.88	0.984
7	34211.01	0.98	84159.01	0.992
8	34227.64	1	84175.64	1
9	31421.25	1.089	81369.25	1.034
10	32118.06	0.978	82066.06	0.992
11	37318.14	0.861	87266.14	0.94
12	41659.06	0.896	91607.06	0.953
13	40882	1.019	90830	1.009
14	45608.37	0.896	95556.37	0.951
15	47056.41	0.969	97004.41	0.985
16	49327.75	0.954	99275.75	0.977
17	48972.09	1.007	98920.09	1.004
18	47074.77	1.04	97022.77	1.02
19	49947.38	0.942	99895.38	0.971

Table 1 shows the sequence values and stage ratios. If all the level ratios are in the interval (eA(-2/(n+1)), eA(2/ N +1)), it indicates that the data are suitable for model construction. If the order ratio test is not passed, the sequence is "translated" to satisfy the order ratio test.

It can be seen from the analysis in the above table that all the level ratios of the sequence after translational transformation are located in the interval (0.905, 1.105), indicating that the sequence after translational transformation is suitable for the construction of the grey prediction model, which is shown in table 2.

Table 2. Grey model construction

The development coefficient a	Grey action b	A posteriori difference ratio C value
-0.012	79063.55	0.286

Table 2 shows the development coefficient, gray action, and posterior difference ratio. The grey prediction model can be constructed from the development coefficient and grey action.

The development coefficient represents the development law and trend of the sequence, and the grey action reflects the changing relationship of the sequence. The posterior error ratio can verify the accuracy of grey prediction. The smaller the posterior error ratio is, the higher the accuracy of grey prediction is.

As shown in Table 2, the posterior error ratio is 0.286, indicating the high accuracy of the model.

Table 3. Table of model fitting results

n index entry	The original value	Predictive value	residua	The relative error (%)
1	35816.17	35816.17	0	0
2	37313.18	30646.252	6666.928	7.867
3	38324.87	31631.477	6693.393	7.465
4	31686.55	32628.745	-942.195	2.973
5	32160.91	33638.205	-1477.295	4.593
6	33536.88	34660.004	-1123.124	3.349
7	34211.01	35694.295	-1483.285	4.336
8	34227.64	36741.229	-2513.589	7.344
9	31421.25	37800.962	-6379.712	20.304
10	32118.06	38873.649	-6755.589	21.034
11	37318.14	39959.449	-2641.309	7.078
12	41659.06	41058.523	600.537	1.442
13	40882	42171.032	-1289.032	3.153
14	45608.37	43297.141	2311.229	5.068
15	47056.41	44437.017	2619.393	5.566
16	49327.75	45590.826	3736.924	7.576
17	48972.09	46758.741	2213.349	4.52
18	47074.77	47940.932	-866.162	1.84
19	49947.38	49137.576	809.804	1.621

Table 3 shows the prediction results of the grey prediction model.

The average relative error of the model is 7.217%, which means that the model fitting effect is good, which is shown in Fig.1.



Figure 1 Model fitting prediction graph.

Therefore, the historical prices of gold and Bitcoin are substituted to predict the trading prices of the next trading day, respectively. The trading price forecast of a trading day in the data given in the question is taken as an example to predict, which is shown in Table 4.

Table 4. Price forecast of a trading day

Period value	i=1	I=3	i=5	i=7	i=9	Average value
Gold price forecast	1787.49	1780.33	1780.01	1763.01	1760.58	1774.28
Bitcoin price forecast	48579.62	49540.62	50348.85	49316.91	50733.05	49703.81

We take gold as an example and use Excel and Matlab to make statistics on the data [4]. The specific implementation process is as follows:

Calculating each financial product's actual price rise or fall on each trading day compared to the previous trading day, M=0.000205.

Calculating the median of all increases M_1 =0.0042.

Calculating the median of all declines M_2 =-0.0044.

The association rule algorithm was selected to calculate the number of subsets of price rises or falls for 2, 3, 4, 5, and 6 times in a row in the set of original price rises or falls, and the corresponding rise was denoted as m_2, m_3, m_4, m_5, m_6, the corresponding decline is called theta l_2, l_3, l_4, l_5, l_6, which is shown in table 5.

Table 5. Association rule algorithm

m_2	m_3	m_4	m_5	m_6	l_2	l_3	l_4	l_5	l_6
345	172	87	39	20	297	155	85	47	25

Calculating the total number of all rising or falling subsets and calculate the number of continuous rising and falling occurrences when the sum of the number of subsets reaches the total number of subsets in the sequence from small to large, denoting as q_1.

For historical data, each rise or fall is calculated as the upper 90% of all gains, and the lower 90% is declined. Next, we will build a gold investment strategy model [3]. We remember the number of consecutive ups and downs, and the financial product calculates the number of consecutive ups and downs according to the sequence from small to large of the number of consecutive ups and downs. When the sum of the number of subsets reaches the total number of subsets, the corresponding number of consecutive ups and downs is, the maximum cumulative increase is, and the maximum cumulative decline is $M_{10\%}$.

In the absence of other circumstances, if the price rises or falls by the same amount each time, and when the price level falls by exactly the same amount after the fall, the additional purchase is made on each fall. Moreover, if the price rises on the next trading day, which achieves profit. In order to

obtain accurate calculation results, we need to consider the factor of transaction cost and deduct the transaction cost in a lump sum after additional purchase, which can be expressed as:

$$\left[A_2 \times M_1 + A_1 \times \left(\frac{M_{10\%}}{q_1}\right) \times M_1\right] \times (1 - 1\%) = 0 \tag{3}$$

The third additional purchase amount is A_3, which can be expressed as:

$$\left[A_3 \times M_1 + A_1 \times \left(\frac{M_{10\%}}{q_1}\right)^2 \times M_1\right] \times (1 - 1\%) = 0 \tag{4}$$

In this way, the additional purchase amount is A_n, which can be expressed as:

$$\left[A_n \times M_1 + A_1 \times \left(\frac{M_{10\%}}{q_1}\right)^2 \times M_1\right] \times (1 - 1\%) = 0 \tag{5}$$

That is:

$$\left[\sum_{i=1}^{n} A_i \times \left(\frac{M_{10\%}}{q_1}\right)^{n-i} \times M_1\right] \times (1 - 1\%) = 0 \tag{6}$$

According to the values obtained in the above process, the corresponding data can be obtained in table 6.

Table 6. Table of the amount added

Add warehouse number	1	2	3	…	n
Accumulating amount	A_1	-0.007425 A_1	0.000055130625		(-0.007425) $^{n-1}$*A_1

Due to the complexity of directly solving the data in the table above, in order to simplify the data processing process, we choose to use the linear regression model to fit the relevant parameters, and the results are as follows:

$$y = ab^t \tag{7}$$

On this basis, we can obtain the normal position management model, and the analysis is as follows. If we assume that when the price rises or falls consecutively, the cumulative rise or fall is:

$$y_\alpha = \alpha e^{\left(\frac{wq_1}{M_{10\%}}\right)} \tag{8}$$

$$y_\beta = \alpha e^{\left(\frac{wq_1}{M_{90\%}}\right)} \tag{9}$$

where α stands for buy and β stands for sell.

To sum up, we can get the buying and selling strategies of gold. Combined with the price trend prediction model obtained in the first part, the prediction can make the trading strategy obtained by us have higher stability. Similarly, we can figure out the trading strategy of bitcoin.

We stipulate that the initial transaction amount of gold and bitcoin are, respectively:

$$A_{gold} = \frac{1000}{2q_1} = \frac{500}{q_1} \tag{10}$$

$$A_{bitcoin} = \frac{1000}{2q_2} = \frac{500}{q_2} \tag{11}$$

We performed further validation using the above model based on the data provided. After the above analysis process, we can draw the following conclusions: the proposed prediction model has high stability. In terms of the formulation of trading strategies, we can adapt to the short-term financial market environment according to the above model, match the optimal trading strategy [5], and avoid trading risks to a certain extent.

3. Sensitivity Analysis

We believe that the change in transaction price essentially depends on the change in transaction cost. Therefore, we explore how changes in traders' returns affect trading strategies and results by changing transaction costs. When transaction costs change, the results we get are significantly different. Through the change of transaction cost, get different regression trading strategy expressions and then calculate the average profit value of traders corresponding to various situations.

For the convenience of exploration, we take gold as an example and take transaction costs of 0.2%, 0.5%, 0.8%, 1.1%, 1.4%, 1.7% respectively. Repeat the steps of trading strategy formulation.

According to the data, we can draw the following conclusion: when the transaction cost changes, the corresponding trading strategy will also change, and the average profit of traders will decrease with the increase of the transaction cost.

4. Conclusion

In this paper, we examine the trends in gold versus Bitcoin. It is found that the grey forecast model error is about 5%. The established model can use specific data from previous years to predict the future exchange rate prices of gold and bitcoin, which helps trading investors make optimal buying and selling decisions. Compared to Bitcoin, the price of gold is lower than that of Bitcoin in the later period so that the price of Bitcoin is more volatile than that of gold. The cost per transaction is about 2% of the transaction volume, and the probability of venture capital is 1%.

References

[1] Q. Tianhua, Stock price forecasting based on gray model and ARIMA mode, Computer Age, 2021(10):83-85+89.

[2] L. Lin, Spss data regression analysis and gray prediction, Mathematical Learning and Research, 2021(29):136-137.

[3] H. P. Zhang, J. M. Zhu, Optimal design of multi-stock portfolio investment strategy based on risk diversification, Journal of Henan University of Science and Technology (Natural Science Edition), 2020,48(04):62-70.

[4] J.L. Zhu, Y. Z. Fu, Y. I. Chen, Portfolio model and its application, Computer Technology and Development, 2013, 23(12):168-170+174.

[5] Y. Peng. Research on SSE 50 ETF price prediction and option strategy based on GA-LSTM, Northwestern University, 2021.