RESEARCH ARTICLE

A Diluted Bitcoin-Dollar-Gold Mean Prediction Scheme Based on Periodic Prediction Method

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ABSTRACT This paper introduces a diluted prediction method for bitcoin and gold based on cycle prediction. This method does not need to quantify the external parameters like robot learning and neural network autoregressive model, but mainly uses ARIMA to feedback the parameter values into risk coefficients under the condition of obtaining the optimal solution circularly, and the price prediction of a single period in the future is carried out with a fixed number of samples, thus realizing the high-precision prediction of bitcoin and gold prices. In the application simulation, the real data of bitcoin and gold from 2016 to 2021 are selected. After 1000 times of Monte Carlo simulations, 919 times of the yield is more than 3 times, 157 times of the yield is more than 8 times, and the minimum yield is about 2 times. At the same time, this paper puts forward an investment strategy for this prediction method, which realizes a very safe profit with a final return rate of 6.2 times under the condition of making full use of the prediction risk coefficient. The prediction method and investment scheme bring a brand-new high-precision prediction method and targeted investment strategy with high safety coefficient to all the investors, which has great economic value.

INDEX TERMS ARIMA, periodic method, monte carlo, circulation, white noise, ADF.

I. INTRODUCTION

Bitcoin is known as the gold in the virtual currency. Its huge volatility has attracted countless people to invest [1], [2], [3], [4]. However, its volatility can not only bring huge profits to investors but also bring the possibility of losses [1], [5], [6]. Since the advent of bitcoin, the academic community has never stopped predicting its price. However, no one or organization has ever been able to accurately predict the price of bitcoin.

Gold has been regarded as a general equivalent since ancient times [7], [8], [9], and its price has generally shown an upward trend in time. However, there will also be a rapid rise and fall in the short term. Sometimes it will last for several days, and it will also bring considerable profit or the possibility of loss.

At present, many researchers use the prediction method of quantifying some factors in reality into parameters and bringing them into the model [10], [11], [12]. This method requires complex modeling and improvement, but at the same time, the qualitative and quantitative judgment for emergencies is seriously insufficient, so it is almost impossible to predict the short-term plummet of bitcoin and gold.

Under the current world economic situation, especially the popularity of bitcoin is no longer comparable to that when it was first listed, and Bitcoin has extreme volatility. The time series autoregressive model [13], machine learning and other methods have been used in Bitcoin price prediction, but they still cannot solve the modeling of the external environment. The main reason is that these methods can find out the overall reasons for the changes in Bitcoin prices in the past period by quantifying the changes in the environment and using formulas to explain them, so that every rise and fall can be predicted by using models. However, in this case, how to reasonably quantize the external environment has become a problem that

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cannot be completely solved, so these methods always have shortcomings, unable to predict stably. A new forecasting method that does not need to be based on accurate modeling of external influences is expected by investors around the world.

This paper abandons the traditional quantitative method and forecasts based on the periodic mean value and dilutes the huge deviation caused by the short-term plummet through the periodic mean value. In this method, the ARIMA model is used for prediction, and the current optimal parameter value is obtained by the circulation method. At the same time, the prediction risk coefficient is fed back according to the parameter value.

The Monte Carlo method is a technique that uses random numbers and probability to solve complex problems [14]. Risk analysis is a part of almost every decision we make because we often face uncertainty, ambiguity, and volatility in our lives. Moreover, even if we have unprecedented access to information, we cannot accurately predict the future. The Monte Carlo simulation makes the prediction results of this paper to be simulated randomly so that we can see all the possible results of the decision and better illustrate the value and feasibility of the prediction method in this paper [15].

The prediction results in this paper have been tested by the Monte Carlo method. After 1000 experiments, the final profit of 919 experiments is more than 3 times, the final profit of 157 experiments is more than 8 times and there is no loss in any simulation result. At the same time, this paper proposes a threshold trading method that is suitable for the cycle prediction method proposed in this paper. It makes full use of the prediction risk coefficient to formulate the trading strategy and achieves a return of 6.2 times.

Experiments show that this method provides a special cycle prediction method for global investors. The prediction accuracy of this method is very high, and it has a prediction risk coefficient. After cooperating with the bitcoin-dollar-gold investment strategy proposed in this paper, it can realize rapid asset appreciation in a few years under a highly safe situation, and has extremely high economic value and practical significance.

II. NEW MATERIALS AND METHODS

A. ARIMA MODEL PRINCIPLES

ARIMA is a classical time series analysis method [16], which is a linear combination of past errors and past values of stationary time series [17]. It is often used in short-term forecasting.

ARIMA is mainly composed of autoregressive(AR) and moving average(MA). AR is an autoregressive model, which must meet the requirements of stationarity. The mathematical expression of p-order autoregressive model is as follows:

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \varepsilon_t \tag{1}$$

IMA is a moving average model, which mainly uses past interference and current interference to predict the actual

value of the model. The mathematical representation of the q-order moving average model is as follows:

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

The basic prediction method of the model is to arrange the prediction objects according to the time series, and then use a certain mathematical model to describe the arrangement. When the mathematical model is finally identified, the future value can be predicted. ARIMA prediction can be expressed as:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t \tag{3}$$

Due to the characteristics of ARIMA, it has great deviation in long-term time series prediction, so ARIMA is currently widely used in various short-term forecasts, such as agricultural product prices, air cargo volume analysis with prediction, and price prediction of some stocks. However, at present, the prediction of sudden group time is always limited, such as the September 11 Attacks, the outbreak of war, etc., so ARIMA's prediction of mining collapses and large declines in a single day has always had a lot of error [18].

B. DATA SOURCE AND PREPROCESSING

As a classical time series prediction model, ARIMA still has a large error in long-term prediction and it is difficult to solve this problem by existing technical methods. Given the above situation, we adopt the following settings: the number of predicted data is set to 1, the number of samples for prediction is fixed, and the model is continuously adjusted by changing the parameter value to achieve maximum accuracy. The method of changing parameters will be discussed in detail below. For the original price data, we select the bitcoin and gold prices from September 11, 2016, to September 10, 2021. The gold price is from the statistical data of the London Bullion Market Association, and the bitcoin price is from the statistical data of NASDAQ. We mainly study the daily trading prices. So far, we have obtained 1826 data each for bitcoin and gold, of which the price data of bitcoin will change every day. The price data of gold is the continuation of the cut-off price on Friday because of the time when the market is closed.

We first made preliminary statistics on the rise and fall of the two. The results show that the rise and fall of bitcoin are several times more severe than that of gold. The following is the trend and the rise and fall of the two:

We have made statistics on the plummeting situation of the two. The main statistics are the number of days with daily increase and decrease exceeding 5% and the number of days with daily increase and decrease exceeding 10%, as shown in the following table. At the same time, the decline of bitcoin is more than 15% in 4 days, and the highest decline of gold is only 5.1%. The volatility of bitcoin is much greater than that of gold. Investing in bitcoin will bring higher income,
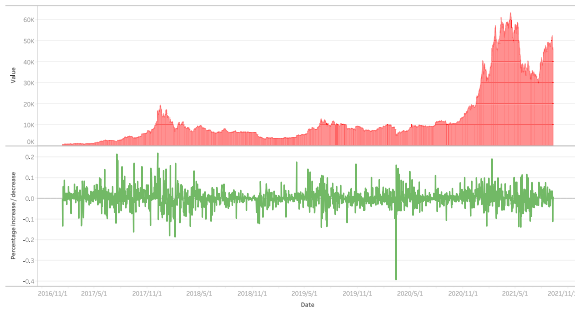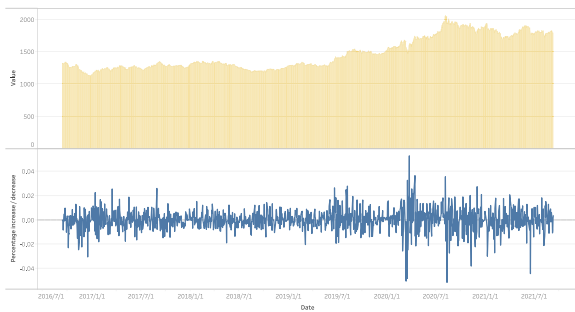
FIGURE 1. Bitcoin trend and ups and downs.

FIGURE 2. Gold trend and ups and downs.

TABLE 1. Statistics on the rise and fall of bitcoin and gold.

Date	Bitcoin	Goldn
>5%	157	1
>10%	38	0
<-5%	128	2
<-10%	28	0

and also bring much greater volatility risk and loss than that of gold.

Therefore, predicting the price of bitcoin and improving the accuracy is the fundamental condition for improving the revenue. At the same time, the price of bitcoin fluctuates. When the fluctuation occurs, the prediction method proposed in this paper will automatically return to the prediction situation, stop bitcoin trading at any time and turn to gold trading. Therefore, the price prediction for gold is also required. In this paper, gold will be mainly used as an additional product after the prediction of the bitcoin price, as well as the main investment and asset appreciation means when the bitcoin prediction model feed back the predicted risk.

C. PARAMETER DETERMINATION
If ARIMA is used and the prediction value with minimal error is required, the parameter values of p, d and q in the formula need to be confirmed. Where d is the difference order, and the stationarity test is required. If the original sequence is stable, d is directly set to 0; If the original sequence is unstable, the original sequence needs to be transformed into a stable sequence after the difference algorithm, so as to continue the time series prediction. The parameter pq mainly needs to pass
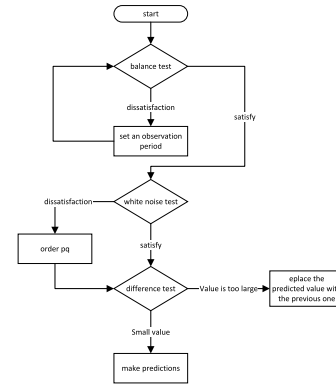

FIGURE 3. ARIMA parameters determination flowchart.

the white noise test. If the white noise test passes, pq is set to 0; If the white noise test fails, it is necessary to cycle and optimize pq. Only after the three parameter values of p, d and q are established through the above process can ARIMA be officially used for time series prediction. The overall flow chart is as follows:

In order to ensure the feasibility of the model, we first test the stability of the sequence. ARIMA's characteristics make it can only be applied to stationary sequences. When encountering unstable series, we must use methods such as difference to convert them into stationary series before time series prediction [19], [20], [21].

It should be noted that all cycles used in this paper change dynamically with the number of days, that is, the data contained in the cycle will be updated continuously with the increase of days. Every time the number of days increases by five, the number of cycles will increase by one. For gold, the price of the weekend is equal to that of Friday and does not appear in the sequence. Therefore, the price of gold is repeatedly arranged from Monday to Friday, and its cycle has remained unchanged for five days, but the update rule of cycle number is consistent with that of bitcoin cycle. The commonly used stability tests include Augmented Dickey-Fuller (ADF) test and Phillips and Perron(PP) test [22]. This paper will use ADF for testing, which can be expressed as:

$$\nabla X_t = \gamma X_{t-1} + \xi_1 \nabla X_{t-2} + \xi_{p-1} \nabla X_{t-p-1} + \varepsilon_t \quad (4)$$

We have conducted ADF test on bitcoin and gold respectively. When the return value is less than 0.05, it means that the series is a stationary one, and if it is greater than 0.05, we need to convert it into a stationary series by means of difference and other methods. Every time we run a cycle, we will add one to the sample set. The test results are as follows:

It can be seen from the figure that for bitcoin, the ADF test results of most of the sample data in the cycle after difference meet the requirements within 0.05. The ADF noise of the sample data in part of the cycle is still very large after 9-order difference on consecutive days, indicating that it is still not stable, so we will replace the prediction data of these large
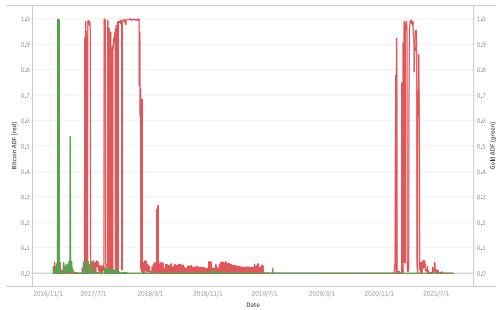
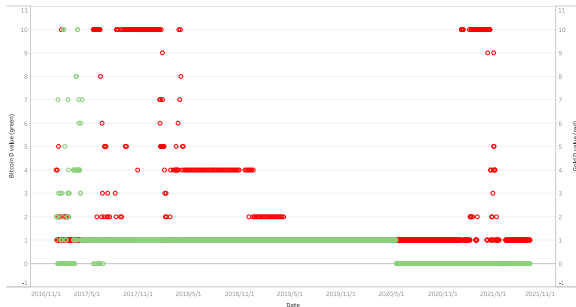**FIGURE 4.** ADF test results of bitcoin and gold.

FIGURE 5. Determination of d value of bitcoin and gold.

samples with the latest day's data in the sample. So is gold. We record the difference order of the data with stationarity after the difference test.

The difference order is mainly achieved by the algorithm's automatic cycle optimization, that is, when the return value of the stationary ADF test is less than 0.05 after the d value meets a certain value, the d value at this time is recorded as the parameter value. It is not difficult to judge from the above figure that the d value is directly related to the ADF test value. The sample data with too large ADF return value is the sample data that still does not have stability after 10 order difference, and the sample data with larger d value is applied at the same time. However, the deviation in the future cycle price prediction is great. This point will be discussed later. After determining the stability, in order to decide whether there is a need to determine the order, we also carried out white noise detection [23], [24], [25]. This detection is mainly used to determine the order through acorr-ljungbox function. The white noise test mainly needs to meet the following three conditions:

$$E(\varepsilon_t) = \mu \; Var(\varepsilon_t) = \sigma^2 \; Cov(\varepsilon_t, \varepsilon_s) = 0, t \neq s \quad (5)$$

When the p value returned by the function is less than 0.5, then the sequence at this time is a stationary non white noise sequence, which means that it is outside the 95 percent confidence interval. It is necessary to determine the order, that is, traverse the p and q values in the model to find the best value; If the return value is greater than 0.5, it means that it is within the 95 percent confidence interval. There is no need to determine the order. Just set the order of p and q to 0. The white noise test results of each cycle sample data of gold and bitcoin are as fig6.
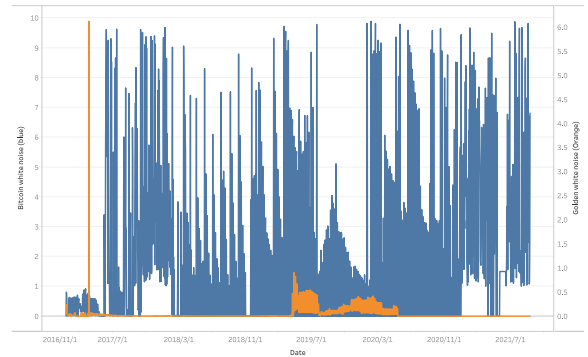

FIGURE 6. White noise test results.

If it does not meet the white noise test, it needs to rank (p, q). For the prediction results, it is found that a large value in (p, q) will be accompanied by a great deviation. Therefore, a conservative strategy is adopted. Any prediction data greater than 5 in (p, p) is replaced by the latest one-day data in the sample. For better (p, q) values, record them for ARIMA prediction.

D. PRICE PREDICTION

After the parameters are determined, we begin to formally use the set value of pdq for future price prediction. Considering that gold is not traded on weekends every week, and in order to improve the accuracy of our prediction, reduce the error as much as possible, and fully consider the price characteristics of gold and bitcoin in the past time period, this paper introduces a diluted prediction method, that is, by calculating the average value of prices over multiple days, the average value of prices in the next cycle is predicted through the first n average values each time, so as to dilute the impact of the short-term slump to the greatest extent. At the same time, our experiments based on the literature show that it is not feasible to infer the plummet date and the mining accident date through modeling, so we can only take the dilution method to reduce the impact of the plummet.

The specific implementation of the dilution method is: set the number of days x contained in a range, take y days as a cycle, and take the average price of each cycle as a sample, that is, use x/y samples to predict the average price of the next y days, and then take the average price of the forecast as our forecast price for tomorrow. We first take several existing past prices as samples to speculate on prices in the next cycle.

For bitcoin, take 3 to 7 days as a cycle, and use ARIMA to predict the average value of the cycle. This method can greatly reduce the impact of mining accidents and plummeting. At this time, we need to enter a cooling off period first. During the cooling off period, we only collect exchange rate data every day without action. This time can be calculated by the following formula:

$$Cooling \; off \; period = Number$$
$$of \; cycles * Number \; of \; days \; in \; a \; cycle \quad (6)$$

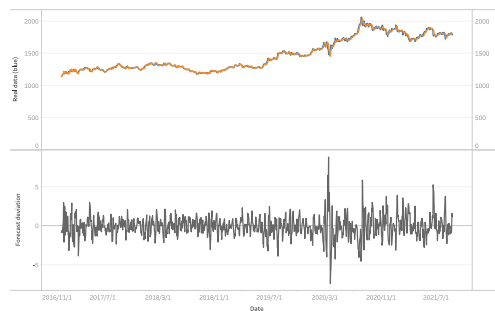**FIGURE 7.** Average deviation of bitcoin prediction.

FIGURE 8. Average deviation of gold forecast.

According to the experience summary of the article [26], there is no cyclical feature for bitcoin and gold. At the same time, when making cyclical forecasts, the number of days in a cycle should not exceed seven days, and should not be less than three days at the same time, otherwise the efficiency of diluting the impact of the slump will be greatly reduced. If it exceeds seven days, the effect similar to nested time series prediction will be caused by too many days, which is bad. Therefore, we choose 3 days, 5 days and 7 days as a cycle, and 10, 6 and 5 cycles as a prediction sequence to predict. The cooling-off period is 30 days, 30 days and 35 days respectively. The results show that when the period is 5, the relative deviation is smaller, and the overall deviation is relatively stable, but the overall deviation of the three is large, so the strategy needs to be improved.

In the previous test, we finally selected the five days with small average error as the prediction cycle of both, and this number of days is also the number of days in a gold trading cycle. In the cooling-off period, we set a 24 cycle cooling-off period for bitcoin, a total of 120 days; For gold, we set a cooling-off period of 16 cycles, a total of 80 days. After completing the above settings, we began to improve the price forecasts for both.

In terms of the improvement of bitcoin price prediction, after linking the specific value of pdq with the error percentage, we found that 80 percent of the large deviation occurred when one of d and q was greater than 4, and pdq was 0 in partial date prediction, resulting in an error of about 70 percent or more. Therefore, we have updated the value scheme of d value. The specific rule is: if the difference order d is greater than 4, or (pdq) is zero, we directly replace the predicted value with the latest one-day data in the sample, and feed back an unstable representation to the model, so as to facilitate the real-time adjustment of the verification strategy. The verification strategy will be described in the next chapter. After the above processing, the overall cycle prediction value, real value and deviation value obtained are shown in the figure below.

It can be seen from the figure that the accuracy of price cycle prediction for bitcoin has reached a very high level, with individual burr errors of more than 20 percent, and the cycle mean prediction price errors of more than 95 percent of dates

are within 10 percent. For bitcoin, which has no periodicity at all and has a lot of emergencies, the prediction with an error of less than 10 percent has great application value.

Due to the linkage nature of our scheme and the difficulty in predicting the price of gold, we will predict and invest in both at the same time, so as to achieve the purpose of internal circulation and to realize the real practical application value of this prediction. In the prediction scheme for gold, we still use the same processing scheme, which means pdq is 0. We also don't make any adjustment for the case that the two parameters of dq are too high. This is mainly because the price stability of gold is much higher than that of bitcoin. Even if the difference order has a high value, due to its characteristics, we decided to keep the high parameter value for operation, and the results are shown in the figure below:

According to the above analysis, our prediction model has reached sufficient accuracy. The overall deviation for bitcoin is basically controlled within 10 percent, and the deviation for gold is directly controlled within 5 percent, with extremely high accuracy.

E. HORIZONTAL COMPARISON OF PREDICTION

On the prediction scheme of Bitcoin, the mainstream now uses trained neural networks for prediction. In this prediction scheme, the Neural Network Autoregressive Model (NNAR) has high accuracy, but the NNAR has been proved to be less accurate than ARIMA in the prediction of fluctuating Bitcoin prices. See reference [13] for details. At the same time, there is a great possibility of distortion in the single-day long-term price prediction of Bitcoin. It is also proved that it is not feasible to predict the transaction price of multiple future trading days based on the transaction data of previous days. See the literature [13] and [26]. If we want to make a reliable forecast against the special currency, we can only make a limited number of daily price forecasts. At the same time, the literature also analyzed the number of samples. It is obvious that when the number of samples is too large or the samples are increasing, the deviation obtained will increase with the increase of the number of samples. Therefore, only by fixing the number of samples and keeping them unchanged can we achieve better prediction accuracy.

At the same time, machine learning has also been applied at this stage. Econometric models and machine learning methods have also been used in Bitcoin forecasting [26]. The above references mainly use RNN, GARCH, and EWMA. The final error is about 10%, which is relatively high. But it is necessary to learn and model peripheral data in advance, so there is a shortage in dealing with unexpected events.

However, the method proposed in this paper does not need to model the external situation. It only needs to predict the future cycle based on the transaction data of Bitcoin in the past period, which can better avoid the impact of unexpected events. This can be observed from the prediction results given above. The prediction method in this paper can still maintain a basic deviation of about 5% in the violent turmoil of Bitcoin in 2020-2021.

To sum up, the method proposed in this paper realizes the high-precision prediction of extreme fluctuations of Bitcoin prices while avoiding the complex modeling of the external environment.

F. TRANSACTION RULE SETTING
For the prediction results, we need to apply trading strategies to test. Considering that bitcoin and gold trading in US dollars need to pay a certain handling fee, our trading rules set that trading is allowed only once a day. Take bitcoin as an example. When we buy bitcoin and gold with a certain principal, we will get bitcoin and gold with the following values on the same day. According to the actual situation, we set the handling charge of bitcoin to 2 percent and the handling charge of gold to 1 percent.

$$Post - purchase\ value = principal * (1 - premium) \quad (7)$$

Because the handling charge of bitcoin trading is very high, we can only buy and sell once a day in this model. If there is a gold-bitcoin or bitcoin-gold transaction on that day, the transaction needs to be converted from the first currency into US dollars and then into the final currency. At this time, the residual value can be calculated directly. The first formula is the residual value after converting a certain amount of gold into bitcoin, and the second formula is the residual value after converting a certain amount of bitcoin into gold:

$$Post - purchase\ value = principal * 0.99 * 0.98 \quad (8)$$

III. EXPERIMENTAL RESULTS AND ANALYSIS
Because this paper uses the diluted prediction method to reduce the impact of the deviation caused by the plummet of special dates through the average value of the period [28], it is unreasonable to use only the traditional mean deviation test method [29], such as the recall rate, accuracy rate and F1 score [30], [31], [32]. For the prediction scheme proposed in this paper, we first use the Monte Carlo simulation method to evaluate. According to the evaluation results, we propose an improved threshold trading method, which takes the parameter value of ARIMA prediction as the risk coefficient to finally determine the gold-dollar-bitcoin trading strategy.

It should be noted that this method is only applicable to the periodic prediction method proposed in this paper. After testing, it is proved that the prediction strategy proposed in this paper is effective and has certain practical value.

A. STRATEGY DESCRIPTION
By comparing the pretreatment curves of bitcoin and gold in the previous text, it is not difficult for us to draw the following conclusion: in the gold-dollar-bitcoin linkage investment, more bitcoin investment activities should be carried out to obtain higher returns. The premise of this investment is that the prediction is very reliable and accurate; If you want to obtain a stable high return, you should consider reducing bitcoin transactions as much as possible and improving gold transactions when the prediction reliability is not enough. It can be seen from the introduction of this article that pure investment in bitcoin is extremely risky, and the accurate prediction of bitcoin cannot be realized. Therefore, our strategy will be based on the premise of reasonably pursuing advantages and avoiding disadvantages, and the final scheme will not be pure bitcoin investment.

Based on the prediction above, we add the following rules here:When the parameter value is found to be too large in the prediction of bitcoin, it is deemed that the prediction result is unreliable. If it is found that the predicted price of the next cycle is lower than the price of the current day, it is mainly considered to sell bitcoin (if there is a bitcoin position) or buy gold (if there is no bitcoin position). Under this rule, we fully take the uncertainty in the investment into account, making it more realistic.

In terms of specific purchase strategies, this paper mainly focuses on the comparison between the predicted price of gold and bitcoin in the next cycle and the price of the current day and adds the accuracy prediction obtained in the model prediction to make the purchase and sale decision. The main rules are as follows: when there is a substantial price increase, buy more when you are guaranteed to have a certain percentage of the minimum amount of cash. When there is a small price increase, buy less when you are guaranteed to have a certain percentage of the minimum amount of cash. When there is a substantial price reduction, sell most of them. When there is a small price reduction, sell a small part of them. At the same time, we add weekend judgment. If it is on weekend, even if gold is predicted to rise or fall, we choose not to buy or sell. If it is on weekdays, then we can trade.

In the overall environment setting, we set the initial capital as $1000, 0 bitcoin position, and 0 gold position. The final results of all tests are the dollar value of all positions at the end of the test, without considering the conversion fee.

B. MONTE CARLO SIMULATION METHOD
Monte Carlo simulation is a technique used to understand the impact of risks and uncertainties in the financial sector, project management, cost, and other predictive machine learning models. This method is used to prove the feasibility of the proposed prediction scheme of bitcoin and gold.
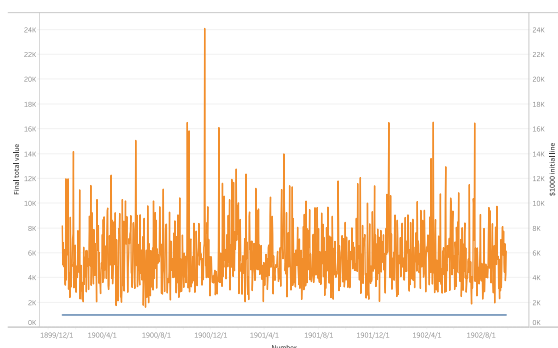
FIGURE 9. Monte carlo simulation results (1000 times).

Because the investment is full of risks and uncertainties, the Monte Carlo simulation method is very suitable for our experiment.

We first set a range of random values for the Monte Carlo method. Considering that gold and bitcoin have transaction fees, we set the buying threshold of both sides between 0.01 and 0.3, the selling threshold of both sides between −0.01 and −0.3, the buying ratio of small rise is set between 0.01 and 0.2, the buying ratio of large rise is set between 0.2 and 0.4, the selling ratio of small fall is set between 0.01 and 0.2, and the selling ratio of big fall is set to 0.2-0.4. The accuracy of random value is set to 0.01.

In this experiment, the threshold of random buying and selling of bitcoin and gold and the threshold of buying and selling ratio are used in each transaction. See the above for the threshold setting. However, it is still affected by the prediction reliability, that is, when one of the best prediction parameter values returned by ARIMA is greater than 5, the bitcoin buying will still be reduced, and the gold trading tendency and bitcoin selling tendency will be increased.

Under this setting, we conducted 1000 simulations, collected the gold-dollar-bitcoin quantity at the end of each simulation, and converted it into US dollars through the exchange rate of the day without calculating the service charge, as shown in the following figure:

According to the 1000 times Monte Carlo simulation data, the diluted periodic prediction method proposed in this paper has absolute practical value, and there is no loss in all simulation results.

Among them, the maximum value is 24103.3813458098 US dollars, and the minimum value is 1627.58271957496 US dollars. Among 1000 times, the final value of 919 times is more than 3000 US dollars, the final value of 157 times is more than 8000 US dollars, and the final value of 56 times is more than 10000 US dollars, achieving ten times of profit. Next, special strategic improvement is needed to make the overall investment improve the rate of return as much as possible while maintaining high safety. However, stability and safety are still the first consideration.

C. IMPROVEMENT PLAN

The previous text has proved that the prediction method proposed in this paper has absolute practical value. In this

section, a threshold trading method applicable to this strategy will be proposed to achieve the maximum return investment strategy under the condition of fully considering the prediction reliability and risk coefficient.

Since the premise of using the cycle prediction method is to collect the initial sample data, the transaction cannot be conducted during the initial sample data collection process. We call it the cooling-off period. We need 24 cycles to forecast, and the minimum cooling-off period is 120 days. However, we set the cooling-off period for trading as one year, that is, all dates before January 1, 2018, are set as the cooling-off period for trading. The specific reasons are as follows.

In the improved strategy, we first need to get the threshold value of the transaction. As for the threshold value, we mainly adopt the circular method to select the best according to the data of the previous period and then apply it to the next year. This again requires the setting of the cooling-off period. As mentioned above, the cooling-off period predicted is 120 days. Here, we set the cooling-off period obtained by the threshold as 1 year, that is, no transaction occurs before January 1, 2018. All the real data of this year are used as the next prediction and determination of the threshold.

In this paper, the cycle method of sample data is used to determine the threshold. The main methods are as follows: for the whole year of 2017, we do not conduct any trading operations. After the end of 2017, we calculate the trading threshold of the maximum return value based on the real price data of the year and apply this threshold value to the trading strategy for 2018. After the end of 2018, we use this method to obtain the threshold value for 2019. It should be noted that in the process of optimization, a constant threshold value is maintained throughout the year for trading. After the end of the experiment, the threshold value is added or subtracted, and then the next experiment is conducted. Each experiment is from the beginning of the year to the end of the year.

In the process of optimization, we need to compare the floating value with the threshold value. Take t_0 for example, when the average value of t_{0+1} to t_{0+6} is estimated, we can compare it with the price of t_0. If the floating value is higher than the buying threshold value, the buying strategy will be started. If the floating value is lower than the selling threshold value, the selling strategy will be started. All the floating values in this paper are the real values before turning into absolute values. The floating value is calculated as follows:

Floating value = (*Predicted value* − *True value*)/*True value*

(9)

After circular optimization, the optimal transaction threshold for each year is shown in the following table, B means bitcoin while G means gold.

D. RATE OF RETURN

After the completion of the threshold trading method, we need to make a comparative analysis. This paper first

TABLE 2. Best trade threshold per year.

Threshold	2017-2018	2018-2019	2019-2020	2020-2021
B buying	0.03	0.03	0.06	0.04
B selling	-0.25	-0.26	-0.26	-0.26
G buying	0.04	0.04	0.04	0.04
G selling	0.04	0.04	0.04	0.04

TABLE 3. Sales (part).

date	Total asset value	Buy and sell Bitcoin	Buy and sell Gold
2018/3/14	2544.40	-241.81	0
2018/3/29	2382.3	-168.03	133.39
2018/3/30	2258.77	158.45	0
...	...	...	...
2019/11/24	2588.60	134.51	0
2019/12/9	2601.42	161.42	0
2020/2/27	2929.66	64.56	0
...	...	...	...
2021/4/30	8572.04	245.50	0
2021/5/13	8282.54	196.40	0
2021/6/17	7275.07	0	158.72

calculates the maximum return under the condition of using the predicted risk coefficient, that is, using the optimal threshold value of the annual transaction obtained above, and setting the predicted risk coefficient to 0 for trading. The resulting final position value is $2015588, and the yield is 201458%. At this time, the optimal bitcoin buying threshold is 0.02, the selling threshold is −0.02. The buying threshold of gold is 0.06 and the selling threshold is −0.01. The yield formula is as follows:

$$Yield = (Grossvalue/Initialvalue - 1) * 100\% \quad (10)$$

After obtaining the maximum value of the rate of return, we simulated the real situation. After the predicted risk coefficient is restored to the original value, the final position value is $3498 and the yield is 250%. At this time, the optimal bitcoin buying threshold is 0.1, the selling threshold is −0.15, the gold buying threshold is 0.02, and the selling threshold is −0.04. The specific dates of buying and selling are as follows:

IV. CONCLUSION

This paper uses ARIMA as a prediction tool for bitcoin and gold [33]. The impact of the plummet is reduced by the periodic dilution method, the value of d in the model parameters is determined by the ADF test and seizure, the value of pq in the model parameters is obtained by the white noise test and the cyclic optimization of the sample data characteristics, and the parameter value is fed back as the risk coefficient. Finally, the accurate prediction that the general deviation of bitcoin does not exceed 10% and the general deviation of gold does not exceed 5% was realized.

For the predicted data, through 1000 times of Monte Carlo tests, there was no loss, and more than 90% of the simulation results showed a triple return. Subsequently, this paper proposes an investment method based on the threshold trading method, which realizes a return of 6.2 times under the condition of fully considering the risk coefficient, and provides a special and high-precision prediction method and a stable investment method for investors around the world.

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