**Problem Chosen** C

**2022**

**MCM/ICM**

**Summary Sheet**

**Team Control Number** 2212336

**The Queen of Strategy: The Road to Counterattack With $1,000**

**Summary**

Nowdays, financial activities have become an important part of people’s lives. In trad ing, some people end up making profits but some people lose money. The differences be tween the losers and the profiteers are not only for the choice of asset variety, but also for the trading strategy. In this paper, we focus on the development and evaluation of strategies. For this purpose, we designed two models to develop our strategies: Model I: Volatile Asset Price Forecasting Model; Model II: Strategy Improvement Model.

For Model I, as a forecasting model, the accuracy of its results is relevant to the formula tion of our strategy and its returns. It is prudent to predict only one day ahead in a single run. We first use the ARIMA model to forecast the price and find that it can only predict well about the linear part of bitcoin price. Second, we take the LSTM model to forecast, and just the opposite of the ARIMA model, the LSTM model is able to capture the information of the non-linear part of the asset price relatively well; finally, we combine them to form ARIMA LSTM model, and the final price prediction results almost overlap with the real results, with RMSE and MAPE were 0.0342 and 0.36, respectively.

Second, to develop the strategy, we used the dynamic programming method to split the five-year-long investment strategy problem into smaller problems of daily investment deci sions. After programming using MATLAB, we calculated the value of the initial money as $374,563.25 on 9/10/21 and discounted this value to five years ago to obtain $360,595.32, which means that the value of $374,563.25 on 9/10/21 is equivalent to the value of $360,595.32 on 9/10/16. This results in a return of 37456.33%.

For Model II, we decided to use genetic algorithm to improve the original strategy as we found many opportunities were missing. We created 4 genes, namely trading portfolio, trad ing frequency, buying strategy, and selling strategy, hoping to improve our strategy from these four dimensions. After MATLAB solving, we learned that the initial capital was valued at $442,697.25 on 9/10/21 and after discounting it was $426,188.16, creating a total yield of 44269.73% ,an annualized return of 338.08%.

Again, we demonstrate that our strategy is optimal in two ways, one by changing the strategy itself and the other by observing different market environments. To change the strat egy, we reset gene4 in the genetic algorithm. After running the results, we found that the yield after the change was reduced to 273%. To observe the strategy performance in differ ent market environments, we extracted the bull, bear and oscillator markets that existed in five years, using bitcoin trading as an example. Comparing the strategy performance and the market performance during the periods respectively, we again find that the strategy outper forms the market performance by a wide margin.

Finally, we wrote a memorandum to investors detailing our modeling process, introduc ing our strategy, analyzing the strategy results, and informing about the risks and shortcom ings of the strategy.

**Keywords: ARIMA-LSTM Model, Dynamic Programming, Genetic Algorithm**

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**1 Introduction**

**1.1 Problem Background**

In real world of finance, all buying and selling behaviors are based on people's expecta tions for the future, so how to predict the future price of assets as accurately as possible has become one of the most important research contents in finance. The more accurate the in vestor's prediction of asset prices, the easier it is to achieve higher expected returns.

Of course, it is rogue to talk about returns without risk. Theoretically, in the market, va rieties with higher risk tend to have greater profit. In order to adapt to people's different risk preferences, a wealth of financial products have emerged. Among them, Bitcoin is favored by investors due to its limited total amount, safety, free transaction, wide circulation range and so on. However, due to high price volatility of bitcoin, gold, which is considered as a safe haven capital, is paired with it to form an investment portfolio.

The "best daily trading strategy" described in the subject must have a specific measure ment. It is often said in finance that if investor A is a risk averter and investor B is a risk seeker, we cannot consider investor B's strategy to be superior one even if investor A's return is lower than B's return. Therefore, in this question, our strategy must be based on a given risk preference so that our strategy comparable.

**1.2 Restatement of the Problem**

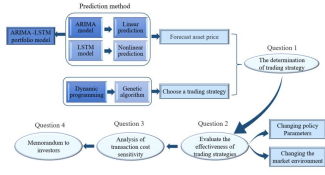
Considering the background information and restricted conditions identified in the prob lem statement, we need to solve the following problems:

 If you have $1000 on 9/10/2016, with known historical prices of the asset, create a model to make an optimal strategy, calculate how much is it worth on 9/10/2021.  Prove that your strategy is optimal in different situations.

 Perform a sensitivity analysis of strategy results between trading costs and de rive how trading costs affect strategy and investment results.

 Writing a letter with traders to summarize your strategy, model, and trading results. **1.3 Our Work**

The flow chart of our idea is shown in Figure 1.



**Figure 1:** Flow Chart

**2 Assumptions and Justifications**

**Assumption 1:** Investor who will use this strategy is a risk-seeker who willing to take arbitrary risk for the sake of return.

**Justification:** As explained in Section 1.1: strategies with different risks are not compa rable. In order to evaluate strategies better, we must assume the risk of strategy, that is, the risk preferences of the investors implementing the strategy. However, since individual risk preferences are difficult to quantify, we make the above assumption that investors are ex treme risk seekers, that is, investor will ignore risk to achieve higher expected return.

**Assumption 2:** Once we decide to trade, we can achieve the deal instantly, regardless of the volume we need to achieve.

**Justification:** In the real world, if there are no enough sellers, then even investors trad ing at current prices may still not be able to close the deal. To simplify the circumstance, we need to make this assumption to rule out this contingency.

**Assumption 3:** No more positions are allowed to be added to an asset while it is held. **Justification:** Position control is a major challenge in investment strategy formulation and is difficult to implement in code. Since Assumption 1 assumes that the investor is a risk

seeker, it is reasonable for us to have a perception that such investor will tend to invest as much money as possible in profitable assets in order to maximize profits, regardless of the risk involved in doing so.

**Assumption 4:** Assume that the minimum transaction unit for bitcoin is 0.1 bitcoins, and the minimum transaction unit for gold is 1 ounce.

**Justification:** In order to match reality as much as possible, and to simplify the diffi culty of programming, we change the minimum transaction unit for bitcoin from 0.01 bit coins to 0.1 bitcoins, and the minimum transaction unit for gold to be consistent with reality.

**3 Definitions and Notations**

**3.1 Definitions**

**Bull Market**：A market with a long-term upward price trend. The overall trend is up ward, with some declines, but one wave higher than the other.

**Bear Market**：A market that has a long-term downward price trend. The overall trend is downward, although there are rallies, but one wave is lower than the other,. **Oscillating Market:** A market situation in which share prices fluctuate and the future of the market is uncertain. It is characterized by an increase in short term investment, unstable market popularity and large ups and downs in prices.

**Position control:** It is your control over the size of your position, and your control over opening, adding, reducing and cutting positions.

**Risk-seeker**: People who prefer to receive the expected income from a risk rather than the expected value of the risk. For a risk taker, the utility of the expectation is greater than the expected utility of the risk itself.

**time value of money**: A certain amount of money currently held has a higher value

than an equivalent amount of money acquired in the future.

**3.2 Notations**

The key mathematical notations used in this paper are listed in Table 1.

**Table 1: Notations used in this paper**

**Symbol Description**

*YT*Asset price in time T

*YT*Predicted asset price at time T

*p*The autoregressive term

*d*The number of differences when the time series is stationary

*q*The number of moving average

μThe constant term

γThe autocorrelation coefficient

*i*

εThe error term

*t*

θ*i*The coefficient of error term

*CFreal*real value by dynamic programming

*d*

*CFno al*nominal value by dynamic programming

min *d*

*r*risk-free yield

*f*

**4 Model I: Volatile Asset Price Forecasting Model 4.1 Volatile Asset Price Forecasting Theory**

According to the question, we need to develop a strategy based on price movements to maximize returns by buying in a lower price and selling in a higher price. Therefore, we need to forecast the daily price in the future first.

In the financial market, different asset prices have their own fluctuation trends and patterns. In order to obtain higher returns, people often build reasonable time series models to predict the future development of volatile assets. Price series forecasting is something that based on historical data, using some scientific method to estimate the price of assets in a certain period in the future. Knowing the time series1 2 3 {Y ,Y ,Y , ,Y }*T*, find the asset price 1 2 3 , , , , *Y Y Y Y T T T T m* + + + +. The formula is shown in equation 1.

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, , , , ( , , , , ) *Y Y Y Y f Y Y Y Y T T T T T* + + + +=(1)

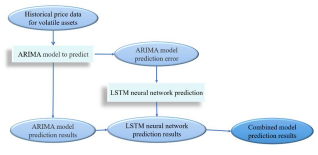
1 2 3 m 1 2 3

**4.2 Volatile Asset Price Forecasting Methods**

The forecasting methods for volatile assets can be divided into linear forecasting models and nonlinear forecasting. Financial markets contain many uncertainties and can be influ enced by economic, political, social factors and so on. The changes caused by these factors have a strong disorderly nature, so it is difficult to say exactly whether it is a purely linear or nonlinear system. Therefore, we need to build a model that contains both linear and nonlinear features.

Traditional time series models can extract linear features, while neural network models

have strong mapping properties for nonlinearity, so our study combines the linear time series forecasting algorithm ARIMA and the nonlinear forecasting algorithm LSTM neural network together for volatile asset price forecasting. the specific structure of ARIMA-LSTM is shown in Figure 2.



**Figure 2:** Model ARIMA-LSTM Overview

**4.2.1 ARIMA Linear Prediction Model**

The ARIMA( , , ) *p d q*model is known as the Autoregressive Integrated Moving Aver age Model, where *p*is the autoregressive term; *d*is the number of differences when the time series is stationary; *q*is the number of moving average items. This model is a combi nation of autoregressive (AR) and moving average (MA), which can transform a non-station ary time series into a stationary time series, and then regress the lagged values of the depend ent variable, the present and lagged values of the random error term to the model established. The formula is given in equation 2.

*p q*

= + + + ∑ ∑(2)

*y y* μ γ ε θ ε − −

*t i t i t i t i*

*i i*

= =

1 1

*y*is the current value; μis the constant term; *i*

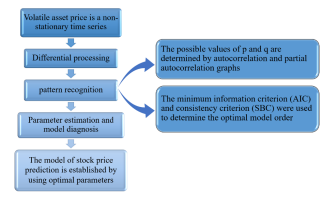
Where *t*

γis the autocorrelation coef

εis the error term; θ*i*is the coefficient of error term. The ARIMA( , , ) *p d q*

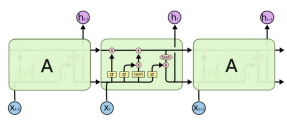
ficient; *t*

model process for furcating asset price is shown in Figure 3.

**Figure 3:** ARIMA Forecast Asset Price Flow Chart

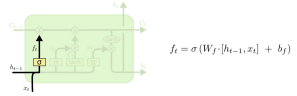
**4.2.2 LSTM Neural Network Nonlinear Prediction Model**

Long Short Term Memory Network (LSTM), a modified recurrent neural network, can handle the problem of long-range dependencies.



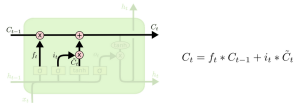
**Figure 4:** LSTM Working Mechanism Flow Chart

The key to the LSTM is the rectangular box in the second elliptical rectangle in Figure 4, which is called the memory block and contains three main gates (forget gate, input gate, output gate) and a memory cell. The horizontal line at the top of the box is called cell state, which is like a conveyor belt that controls the transfer of information to the next mo ment. The two tanh layers in the diagram above correspond to the input and output of the cell. Looking at Figure 4 we can see that the work of LSTM can be divided into 3 main steps. **Step 1:** Decide what information can pass through the cell state. This decision is con trolled by the "forget gate" layer through sigmoid, it will pass or partially pass according to the output of the previous moment. See Figure 5 for details:



**Figure 5:** Step 1 of LSTM

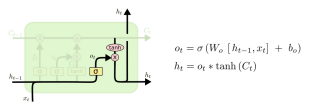
**Step 2:** Generate the new information we need to update. This step consists of two parts, the first is an "input gate" layer that determines which values to update by sigmoid, and the second is a tanh layer that generates new candidates and adds them to the previous candidates to obtain the final candidate values for this part. The two steps are combined to discard the unwanted information and add the new information.



**Figure 6:** Step 2 of LSTM

**Step 3**: Decide the output of the model. The first step is to get an initial output from the

sigmoid layer, then use tanh to scale the value to between -1 and 1, and then multiply the out put with the sigmoid pair by pair to get the final output of the model.



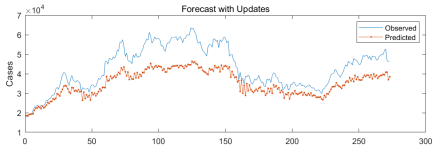
**Figure 7:** Step 3 of LSTM

**4.3 Volatile Asset Prediction Results**

Taking the asset price prediction of Bitcoin as an example, the ARIMA model predic tion and the LSTM neural network model prediction of Bitcoin’s price are performed respectively. The results are obtained as shown below.

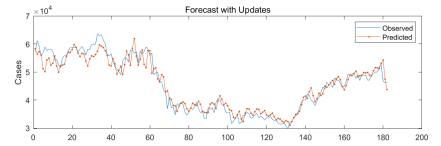
**4.3.1 ARIMA Model Prediction Results**

For this problem, we use the one-step prediction method to predict the asset price, i.e., the first i-1 data are used as the training set when predicting the price of bitcoin at the ith mo ment, while the ith sample is added to the training set when predicting the i+1th sample. The prediction results of the ARIMA model are shown in Figure 8. From Figure 8, we can see that the ARIMA model is not very accurate in predicting the price of Bitcoin, which is especially obvious in the upward trend of Bitcoin price. However, the ARIMA model is still able to capture the trend of bitcoin price changes well, which means that it can predict well about the linear part of bitcoin price.

**Figure 8:** ARIMA Model - Bitcoin Price Forecast Chart

**4.3.2 LSTM Model Prediction Results**

The results obtained by using LSTM neural network for bitcoin price prediction are shown in Figure 9. It can be found that the LSTM neural network model has improved the predict accuracy of the bitcoin price compared to the ARIMA model, and it can capture the fluctuation of the bitcoin price well. Therefore, we can conclude that the LSTM model is able to capture the information of the non-linear part of the asset price relatively well, and we can also find that with the increase of the training set its prediction accuracy will get higher and higher over time.



**Figure 9:** LSTM Model - Bitcoin Price Forecast Chart

**4.3.3 ARIMA-LSTM Model Prediction Results**

To further improve the prediction accuracy, we adopt a combined linear and nonlinear model for prediction. For this purpose, firstly, we based on the ARIMA prediction results and the actual bitcoin price worth to the residual sequence of bitcoin price, which is used as ex pected output of the LSTM neural network; secondly, we phase space reconstruct the original data with a delay time of 1, and finally determine the optimal price number as 7; thirdly, use the data after reconstructing with the optimal order as the LSTM input; fourthly, input the training set to the LSTM neural network for learning modeling and predicting the residual se ries test set to obtain the ARIMA residual series prediction value; finally, the ARIMA and LSTM neural network model prediction results are summed to obtain the final prediction re sult of stock price. The prediction results are shown in Figure 10.



**Figure 10:** ARIMA-LSTM Model - Bitcoin Price Forecast Results

Accroding to Figure 10, it is easy to find that our prediction results are already very accu rate relative to the real values and can be used as the basis for investment decisions. **4.4 Comparative Analysis of Model Forecasting Performance**

In order to verify the superiority of the ARIMA-LSTM-based asset price forecasting model, we use Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE) as the model performance evaluation indexes. The evaluation results are obtained in Table 1. **Table 1:** Model performance evaluation table

Model RMSE MAPE

ARIMA 0.7034 7.21

LSTM 0.6183 6.25

ARIMA-LSTM 0.0342 0.36

By observing the Table 1, it is not difficult to find that: the RMSE and MAPE of ARIMA-LSTM model are very close to 0. Its prediction accuracy is much higher than the prediction accuracy of single ARIMA or LSTM neural network models, and the prediction error is greatly reduced. This is because ARIMA-LSTM combines the advantages of ARIMA model and LSTM model to portray the change pattern of asset price more comprehensively. Therefore, in the part of investment strategy, we will make investment decisions based on the predict results of the ARIMA-LSTM model.

**5 Dynamic Programming Based Trading Strategy Determination 5.1 Dynamic Programming to Determine the Trading Strategy Process**

To obtain the optimal trading strategy, we adopt a dynamic programming algorithm based on the predicted values in the previous section. By splitting the 5-year trading process and defining the relationship between trading states and states, we can solve the problem to in a recursive (or partitioned) manner.

**5.1.1 Splitting The Problem**

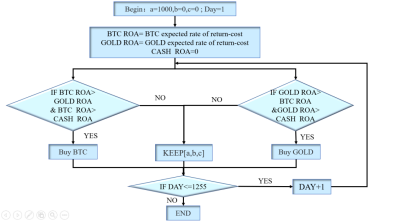
For these 5 years of trading forecasts, we divide the five years in terms of days to get each daily return, for each trading day, we have a triplet like[ , , ] *C G B* , treat each day as a stage, and a daily result can be obtained, so that the problem can be solved by recursion or re cursion.

**5.1.2 Determining The Problem State**

We choose to represent the problem split in the previous section by quantifying it. Since we know the price up to that day (when we make the decision) and the predicted price in 2-3 days, we can make a daily judgment based on the return. With this setup, we end up transforming the big problem into a small problem.

**5.1.3 Dynamic Planning Flow Chart**

Dynamic planning flow chart is as below:

**Figure 11:** Dynamic Programming Flow Chart

**5.2 Dynamic Programming Results**

We obtained Figure 12 of the change in asset value of $1,000 from 9/10/16 to 9/10/21 through dynamic programming and obtained a final estimated asset value of $374,563.25 on 9/10/21.

But since money has time value, we need to discount our terminal value. Since it is com mon in academia to treat the U.S. Treasury bond yield as the risk-free yield, we consider the risk-free yield as the yield on the U.S. five-year Treasury bond on 9/10/16. The discount ing formula is shown in equation 3.

*CF*

*no al*

min

*CFr*

=+ ）(3)

*d*

*real*

*d*

*f*

(1

n

*CFreal*is the real value by dynamic programming, min *d*

Where *d*

*r*is the risk-free yield.

*CFno al*is the nominal

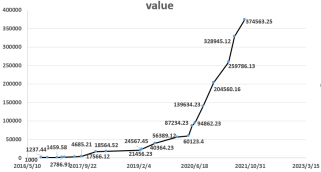
value by dynamic programming, *f*

After calculation, we get that $374563.25 on 9/10/21 is worth $360,595.32 on 9/10/16. The formula for calculating the rate of return is as Equation 4.

( ) *selling price buying price Yeildbuying price*

−

=(4)

Finally, we find that our total return is3745.63%, which is an excellent result. 

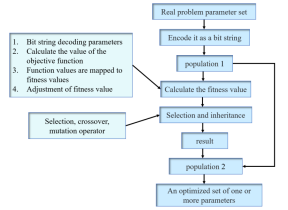
**Figure 12:** Asset Value by Dynamic Programming (2016/9/10-2021/9/10)

**6 Model II: Strategy Improvement Model**

**6.1 Introduction to Genetic Algorithm**

Genetic algorithm is a randomized search algorithm that draws on the natural selection and natural inheritance mechanisms in biology. It simulates the reproduction, crossover and genetic mutation phenomena occurring in the process of selection and inheritance. In each it eration, a set of better solutions is retained, and better individuals are selected from the group of better solutions according to some index; then use genetic operators to combine these indi-

viduals, so that it is capable to produce a better group of solutions; finally, the process will re peat until results converge to the optimal solution.

The operation flow of the genetic algorithm is shown in the figure 13. 

**Figure 13:** The Operation Flow of The Genetic Algorithm

**6.2 Process of Genetic Algorithm Optimization Trading Strategy**

**6.2.1 Encoding**

 **Gene1:** Trading Portfolio Information

According to the question, we know that the trader has an account consisting of cash, gold and bitcoin as [ , , ] *C G B* , but we cannot determine what trading strategy we need to use. So, we set the trading strategy as a non-deterministic variable in our trading system, i.e., Gene1. This variable contains information about which asset will enter our strategy. In this paper, we choose the method shown in the table below to encode it.

**Table 2:** Gene1

C G B Gene1

0 0 0 000

0 0 1 001

0 1 0 010

1 0 0 100

0 1 1 011

1 1 0 110

1 0 1 101

1 1 1 111

In the table 2, the number "0" means that the strategy will not trade on this asset; the number "1" means that the strategy will trade on this asset. For example, if Gene1=101, it means that we will trade on cash and bitcoin. It is easy to see that this table covers all possi ble combinations.

 **Gene2:** Trading Frequency Information

In this article, we create another gene (Gene2) to determine the transaction frequency. The variable Gene2 is used to store our transaction frequency information. Like Gene1, we

use the following rules for coding.

**Table 3:** Gene2

Frequency 1 day 3 days 5 days 7 days 15 days 30 days 60 days

Gene2 000 001 010 100 011 110 111

 **Gene3:** Buying Strategy

There are several strategies for entering the market based on price trends: breakouts of large patterns, breakouts of large averages, breakouts of trends and so on. For example, there are two types of new highs or new lows: one is a new high or new low reached by crossing a historical resistance or support level; the other is a new high or a new historical low that has been reached by crossing a historical high or low in the price run. Once the above breakout is reached, the capital under the corresponding strategy will choose to buy.

Due to the space limitations, we will not describe all the strategies in detail one by one. Depending on the buying strategy, we can code according strategies in order. Rules are dis played as table 4.

**Table 4:** Gene3

Strategies for breakouts

Large Pat terns

Large av

eragesTrendsConsoli dationNew Highs or New Lows

Small Cycle Signal

Gene3 000 001 010 011 100 101  **Gene4:** Selling Strategy

For the selling strategy, we use fixed percentages of loss for the sell operation. We set These stops: 1%, 2%, 3%, 5%, 8%, 10%, as soon as the stop loss is hit, we will sell the asset. We have the following table for the Gene4 code:

**Table 5:** Gene4

Stop Loss Percentage 1% 2% 3% 5% 8% 10% Gene4 000 001 010 100 011 110

These 4 genes can form a chromosome that contains all the choices of our trading strat egy, which contains choices for the dimensions of asset, trade frequency, SMA type, calcula tion period, trailing stop percentage, etc. For our design, the algorithm will first randomly as sign "0" and "1" to each position in the chromosome and then repeat the iterations to create the first generation of chromosomes, in this particular case, each chromosome is a strategy. **6.2.2 Adaptation Function**

The fitness function value is a metric used by genetic algorithms to evaluate the qual ity of the results. The larger the value of the fitness function, the better the quality of the re sult. Although there are many methods to evaluate the goodness of trading strategy selec tion, in this paper only the yield is used as the fitness evaluation func

tion since we only know the asset price price in this problem.

**6.2.3 Genetic Operators**

**Step 1: Selection.** The genetic algorithm uses a selection algorithm to choose individu als with high fitness to be inherited into the next generation population. The roulette wheel selection method is used in the simple genetic algorithm (SGA). Also, backtesting algorithm

is used to perform selection with reading strings, which are then translated into the corre sponding strategies and tested. After testing, the algorithm will give the return of each strat egy.

**Step 2: Mating.**Its main function is to pair the winners selected by the selection algo rithm, which becomes the basis for the next step of reproduction.

**Step 3: Crossover.** It is the process of exchanging some of the genes of two paired chro mosomes with each other in some way based on the crossover probability, so that we can form two new individuals.

**Step 4: Mutation.** There are three possible forms of variation in this problem: genetic variation, strategy swapping and strategy variation.

**6.3 Genetic algorithm to optimize trading strategy results**

After continuous genetic inheritance, selection, crossover and mutation, we get a fitness value (rate of return), which is the optimal solution after genetic algorithm optimization. In this problem, this result is shown as follows.

**6.3.1 Rate of Return**

We plot the returns of each transaction conducted in the five years according to the asset type in Tables 2 and 3, respectively. After observing the tables, we found that Bitcoin has a return of 259.406% in January 2018 and a return of 371.84% in April 2021; on the contrary, the return of gold is more stable and its return does not fluctuate much. **Table 6:** Rate of Return on BTC & Gold

Date Rate of Return on BTC Date Rate of Return on Gold 2017-1-10 44.77%

2017-3-17 29.38%

2017-9-07 120.17%

2017-9-13 70.51%

2018-1-15 259.05% 2018-4-19 0.002919 2018-7-31 0.95% 2019-2-27 0.106942 2019-7-16 174.81%

2019-8-14 5.67% 2020-1-09 0.050922 2020-2-26 0.032783 2020-4-24 0.13822 2020-6-24 0.076138

2020-9-03 0.193441

2021-4-21 3.718426 2021-6-11 0.050733 2021-9-10 0.156693

In the second and third columns of the table, there are some cells with no data in them because there were no transactions made for gold during the period.

**6.3.2 Buy-Sell Time and Price**

Based on the results of the strategy implementation after the genetic algorithm optimiza tion, the buy and sell positions of bitcoin and gold in 5 years are plotted in the figure. The red points are the buy points and the green points are the sell points.

As can be seen from the Figure, our strategy makes a corresponding buy after the price is about to rise or has risen for some time, while the sell points tend to be a small distance

away from the highest point of volatility. This shows that our strategy is well adapted to the market environment.



**Figure 13:** Bitcoin Buy-sell Point Chart



**Figure 14:** Gold Buy-sell Point Chart

**6.3.3 Asset Value Estimation**

After the above discussion, we obtained a graph of the change in asset value of the origi nal $1,000 from September 10, 2016 to September 10, 2021. It was eventually learned that the final asset value on September 10, 2021 was $442,697.25, with a five-year total return of 44,169.70%, an extremely good result compared to bitcoins 7458.97% and golds 135.48% over the same period, with an annualized return of 338.08%



**Figure 15:** Asset Value (2016/9/10-2021/9/10)

After discounting, we get that $442,697.25 on 9/10/21 is worth $426188.16 on 9/10/16. **7 Effectiveness Evaluation of The Trading Strategy**

In the previous section, we have calculated the value that we have on 9/10/21 after im plementing our strategy. To prove that our strategy is optimal in both aspects, we try to change the strategy itself and change the market environment respectively. ` In the previous section, we have calculated the value we have on 10 September 2021 after implementing our strategy. We have attempted to demonstrate that our strategy is opti mal in both respects, in terms of changing the strategy itself and in terms of changing the market environment, respectively.

For changing the market environment, we zoomed in on the market at a particular time, extracting bull, bear and, shock markets, and proved that the strategy outperformed the market over the same period in terms of profitability in either market; for changing the strat egy itself, we set it as a change in the stop-loss strategy, which was used as a proportional stop when we used the genetic algorithm for strategy optimization, in order to verify the In order to verify the validity of the model, we changed it to a capital stop loss, proving that our proposed strategy is better regardless of the stop loss strategy.

**7.1 Bull and Bear Market Strategies**

When evaluating a fund manager, one looks beyond the returns of the fund manager's funds to judge the ability of the fund manager's funds to weather cycles. In layman's terms, this means judging whether the fund manager's portfolio has equally good returns in markets with different environments such as bull, bear and shock markets.

Given that both gold and bitcoin have experienced a full bull, bear and shock market over the 5 years of data given, in order to evaluate our strategy's ability to ride out the cycle, we have extracted the performance of our strategy in bull, bear and shock markets separately and compared it to the market conditions over the same period to draw our conclusions.

Firstly, the performance of our strategy in a bull market is shown in the chart below. As you can see from the chart, we have been able to maintain a holding position during large market rallies and sell assets in time to hedge our risk during some minor fluctuations, which shows that our strategy has also performed well in a bull market.



**Figure 16:** Trading Spots During Bull Market

In the midst of bear markets, it can be seen that we have been in a short position during bad market conditions, while at the lowest point of the bear market, we chose to buy, and our strategy has performed well above the market level over the same period. 

**Figure 16:** Trading Spots During Bear Market

In the midst of an oscillating market, we still managed to buy and sell in a timely man ner and the strategy continued to perform well.



**Figure 16:** Trading Spots During Oscillating Market

**7.2 Stop Loss on Capital**

In gold trading, it is important to set a stop loss. Its main purpose is to help investors manage their investment risk. If an account is losing money, it can be sold to lock in the loss and prevent further declines.

Stop loss levels are used to avoid large price fluctuations by setting a profit and loss point in advance. A capital stop is usually set at a maximum loss that the investor can afford and once the strategy has been implemented, once the loss on a single trade reaches that value, a sell will be made, regardless of expectations.

In operational terms, we simply change Gene4 to Gene4' in the genetic algorithm opti mization of the original strategy. As shown in the table.

**Table 6:** Stop Loss Comparison Table

code 000 001 010 100 011 110 Gene4’ (Stop Loss Amount) 100 200 500 700 1000 1500 Gene4(Stop Loss Percentage) 1% 2% 3% 5% 8% 10% Ultimately, we found that the yield after the change was reduced from 442% is reduced

to 273%, the return of the original strategy is much higher than the return of the current strat egy, so it can be justified that the article is now a more reasonable strategy.

**8 Transaction Cost Sensitivity Analysis**

Transaction costs are one of the key indicators that affect a strategy's yield. Many strate gies have good rates of return under ideal conditions, but may have lower rates of return once transaction costs change. If trading outcomes are more sensitive to transaction costs, it is an indication that the strategy may not be realistic in the face of changing market conditions.

To see the impact of transaction costs on trading outcomes, we replaced the transaction costs with the following four scenarios:

**Table 7:** Table of Changes in Commission

reducing commissions for gold onlyα α *GOLD BTC*

= = 0.5%, 2%

reducing commissions for bitcoin onlyα α *GOLD BTC*

= = 1%, 1%

reducing commissions for both assetsα α *GOLD BTC*

= = 0.5%, 1%

increasing commissions for both assetsα α *GOLD BTC*

= = 2%, 3%

The results are shown in figure 17:



**Figure 17:** Asset Values Under the Influence of 5 Costs

We find that when the commission is reduced on only one asset, the transaction fre quency of the asset with reduced transaction cost will increase. But bitcoin has increased more frequently than gold. The reason lies in the large fluctuation and high frequency of bitcoin, which makes it easier for the price to touch the upper and lower limits set by us when making decisions, so as to initiate buy or sell orders. However, for the final return on assets, the reduction of commission on the two assets will increase the return on assets accordingly.

When the commission of the two assets is reduced simultaneously, we find that the re turn of the asset after the change is greater than the return of the commission of only one as set. Lower commissions on two assets are traded more frequently than if they were reduced on just one asset.

When the commission of two assets is increased at the same time, the final return and trading frequency of the assets are the smallest in the four cases. The reason is obvious. The increase in commissions will reduce our potential profit opportunities, and our capital will be significantly reduced as we trade.

**9 Memorandum to Investor**

Dear Investor:

I am the developer of this investment strategy. There are a few things we would like to tell you about our models, strategies and results. We have used the following models to de velop and improve our investment strategy, which has resulted in good returns.

**Firstly**, we used an ARIMA-LSTM model to forecast the future movement of asset prices. The reason for forecasting is that our investment decisions are based on our expectations, or judgements, of the future movement of asset prices. This forecasting model is the cornerstone of our strategy formulation. The forecasting model is a combination of the ARIMA model and the LSTM model, as both models have strengths and weaknesses that complement each other relatively well; the ARIMA model has a good grasp of the general trend of assets, but lacks the volatility of asset prices, while the LSTM model has the opposite characteristics of the ARIMA model. It was therefore reasonable to assume that the combination of the two would make our forecasts more accurate, and this was indeed the case.

**Secondly**, based on the forecasting results, we use a dynamic programming approach to develop a preliminary strategy. We stand at each point in time and forecast the return for a number of days ahead, buying if the projected return is greater than the commission rate and selling if the loss is greater than the commission. However, such an approach proved to be delayed in capturing price trends and was only sensitive to short, large changes in price move

ments, missing many profit opportunities for nothing.

**Finally,** based on the shortcomings of the original strategy, we proposed to optimise the strategy using a genetic algorithm to improve indicators such as trading time, trading frequency, and stop-loss point settings, ultimately achieving a 440x return, much higher than the returns of bitcoin and gold over the same period.

Our strategy incorporates two assets, one in bitcoin and one in gold. The strategy is, in general, biased towards bitcoin rather than gold. This is because bitcoin tends to be more vol atile in price than gold and its gains tend to be greater than gold, according to forecasts. There fore, when capturing a profitable opportunity in bitcoin over the next few days, we will choose to sell gold at the right place in order to get the bigger gains inherent in the bitcoin trade.

It is worth noting that as an emerging asset, Bitcoin comes with a high level of risk along with a high level of reward. As our strategy is not position-controlled in every trade, but chooses to invest as much of the asset as possible, only the extremely risk-averse will be able to take advantage of our strategy. It is important to note that our strategy does not necessarily trade on a daily basis. Warren Buffett once said, "To be a good hitter, you have to have good balls to hit." This means that we need to be patient and wait for good opportunities rather than struggling to take every swing every chance, and indeed, this is almost impossible for traders to do. We have to give up something to get more. Secondly, our strategies are not foolproof. The vast majority of the time it is not possible to buy at exactly the lowest point and sell at the highest. Investors therefore need to be understanding of this phenomenon.

Finally, thank you for your interest in our strategies and we wish you all the best in life.

Yours sincerely,

Lee.

February 21, 2022

**10 Model Evaluation**

**10.1 Strengths**

⚫ By combining the ARIMA model with the LSTM model, both linear and non-linear situa tions can be taken into account, allowing attention to be paid to both trend changes and volatility.

⚫ The ARIMA-LSTM model can be used to forecast the future trend of stock prices simply by using the evolution of the historical state of the stock itself, which is simple and reliable compared to traditional mathematical and statistical methods.

⚫ The genetic algorithm is applied to the optimization of trading strategies, which not only optimizes existing strategy combinations, but also generates new trading strategies through the evolution of the system, and allows the optimal strategy to be selected for future trading in real time.

⚫ In order to study the effectiveness of the model, we analyze both the two market environ ments and the strategies themselves to make the discussion of effectiveness more compre hensive and reasonable.

**10.2 Weaknesses**

⚫ The financial markets are highly volatile, and the time series analysis method only uses historical price data in the hope of obtaining useful information to predict future move ments, without considering the causes of stock price movements, so it is generally an in tuitive analysis and only makes short term predictions.

⚫ For the strategy combination approach of generating new stocks, because of the single measure taken and the small number of indicators, it does not take into account the differ ent risk-return characteristics of different trading strategies, and the fitness function in this paper only measures the performance over time, without considering the cumulative per formance.

**11 Conclusion**

As our team set out to come up with a strategy on what would be the most efficient way to solve the problem of investment strategy setting. First of all, we should not stand in the perspective of God to invest, and we need to predict the daily asset price. In recent years, the problem of asset price prediction has been realized by many scholars in different ways. We summarize the previous practice, and further propose the method of combining linear and nonlinear models, namely ARIMA-LSTM model. In order to further analyze the strategy set ting, we use the mathematical model of dynamic programming to transform long-term invest ment problems into short-term ones, refine the investment process, and more importantly, we use genetic algorithm to optimize the trading strategy. We proved the effectiveness of the strategy by changing the strategy and changing the market environment. In short, we were

sure that the strategy we proposed was reasonable and effective.

In the following calculation and research, we reasonably extended our strategy and result, studied the impact of commission on strategy and result, and obtained the relationship between commission and them. However, as the title only requires the use of price to set strategies, there are many other factors that affect asset price changes, not only past prices, which can be improved in subsequent studies.

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**Appendices**

| **Appendix 1** |
| --- |
| Introduce: Prediction code |
| a= xlsread('biteb.xlsx');  data=a(:,1)';  TTrain = floor(0.95\*numel(data));  dataTrain = data(1:TTrain+1);  dataTest = data(TTrain+1:end);  sig = std(dataTrain);  Standardized = (dataTrain - mu) / sig;  XTrain = Standardized(1:end-1);  YTrain = Standardized(2:end);  numFeatures = 1;  numResponses = 1;  numHiddenUnits = 200;  layers = [ sequenceInputLayer(numFeatures) lstmLayer(numHiddenUnits) fullyConnectedLayer(numResponses) regressionLayer];  options = trainingOptions('adam', ...  'MaxEpochs',250, ...  'GradientThreshold',1, ...  'InitialLearnRate',0.005, ...  'LearnRateSchedule','piecewise', ...  'LearnRateDropPeriod',125, ...  'LearnRateDropFactor',0.2, ...  'Verbose',0, ...  'Plots','training-progress');  dataTestStandardized = (dataTest - mu) / sig;  XTest = dataTestStandardized(1:end-1);  net = predictAndUpdateState(net,XTrain);  [net,YPred] = predictAndUpdateState(net,YTrain(end));  numTimeStepsTest = numel(XTest);  for i = 2:numTimeStepsTest  [net,YPred(:,i)] = predictAndUpdateState(net,YPred(:,i-1),'ExecutionEnviron ment','cpu');  End  figure  plot(YTest)  hold on  plot(YPred,'.-')  hold off  legend(["Observed" "Forecast"])；ylabel("Cases") title("Forecast") |

| **Appendix 2** |
| --- |
| Introduce: Strategic planning code |
| function [nn,bn,cn,an,sv]=strategy(x,t)  a=1000;b=0;c=0;sx=1;sv=0;nn=[];bn=[];cn=[];an=[];sxf=0;  bite = xlsread('bitezhen.xlsx');  gold = xlsread('goldzhen.xlsx');  by = xlsread('biteyuce.xlsx');  hy = xlsread('goldyuce.xlsx');  [a,b]=bitemai(a,bite(1));  [bl,hl]=shoouyilv(x);  sx=sx+1;  n=1;nn=[nn,n];bn=[bn,b];cn=[cn,c];an=[an,a];  for sx=2:t  if hl(sx)>=bl(sx)  if hl(sx)>-0.01  k=a+b\*bite(sx)\*0.98-gold(sx)\*0.99;  if k>=gold(sx)  a=0;b=0;  [a,c]=goldmai(a+b\*bite(sx)\*0.98,gold(sx));  if a==0  n=2;  else  if bl(sx)>0  [a,b]=bitemai(a,bite(sx));n=4;  else  n=5;  end  end  else  if c>0  if bl(sx)>=0  [a,b]=bitemai(a,bite(sx));n=4;  else  a=b\*bite(sx)\*0.98+a;b=0;n=5;  end  else  if bl(sx)>=0  [a,b]=bitemai(a,bite(sx));n=1;  else  a=b\*bite(sx)\*0.98+a;b=0;n=3;  end |

end

end

else

a=a+b\*bite(sx)\*0.98+c\*gold(sx)\*0.99;b=0;c=0;n=3; end

else

if bl(sx)>-0.02

[a,b1]=bitemai(a+c\*gold(sx)\*0.99,bite(sx));c=0; b=b+b1; n=1;

else

a=a+b\*bite(sx)\*0.98+c\*gold(sx)\*0.99;b=0;c=0;n=3; end

end

nn=[nn,n];

bn=[bn,b];

cn=[cn,c];

an=[an,a];

sv=a+b\*bite(sx)+c\*gold(sx);

end

sv=sv-1000;

nn=nn';

an=an';

bn=bn';

cn=cn';

function [a,b]=bitemai(sv,x)

b=floor(sv\*10/x)/10;n=0;

a=sv-x\*b\*1.02;

if a<0

n=0.1;

while n\*x<(-a)

n=n+0.1;

end

end

b=b-n;

a=a+x\*n;

function [a,b]=goldmai(sv,x)

b=floor(sv/x);n=0;

a=sv-x\*b\*1.01;

if a<0

n=1;

while n\*x<(-a)

n=n+1;

| end  end  b=b-n;  a=a+x\*n;  function [blz,hlz]=shoouyilv(x)  blz=[0];hlz=[0];  by = xlsread('biteyuce.xlsx');  hy = xlsread('goldyuce.xlsx');  for sx=2:1255  if sx-x>0  bl=(by(sx)-by(sx-x))/by(sx-x);  hl=(hy(sx)-hy(sx-x))/hy(sx-x);  else  bl=(by(sx)-by(1))/by(1);  hl=(hy(sx)-hy(1))/hy(1);  end  blz=[blz,bl];hlz=[hlz,hl];  end |
| --- |

**Problem Chosen C**

**2022**

**MCM/ICM**

**Summary Sheet**

**Team Control Number 2218743**

Gold-Bitcoin Market Portfolio Investment Strategy Model and Its Application

**Summary**

In order to obtain higher investment returns and minimize risks, We strive to establish the optimal investment strategy model for effective investment portfolio with two risky assets, gold and bitcoin, and cash, a risk-free asset. The optimal investment decision test and sensitivity test are carried out on the model we established. First, we use the ARIMA algorithm and determine reasonable model parameters based on historical data to predict the asset price of the next day. Considering that too frequent transactions will increase transaction costs, we judge the current market state based on the moving average long-arrangement method, and establishes a trading day selection model with the bull and bear market as the standard. Then, we use the CVaR method to measure the risk of a portfolio. On this basis, we establish the revenue-CVAR dual-objective optimization model, and we use the improved NSGA-II algorithm to obtain a series of feasible portfolios set. Then, combined with the upper limit constraint of the downside semi-variance of the asset portfolio, we obtain the optimal daily trading strategy. Bringing the available data into the built model, we find that the final investment strategy has a 5-year total investment return of 616.63%, an average annual return of 261.41%, and a maximum annual return of 664.69%, which proves that the investment strategy has strong profitability.

Second, we prove that the model provides the optimal investment strategy. In the prediction deviation test, the MAPE values are all less than 0.1 and very close to 0 and the R2-score are all greater than 94% and close to 1. This shows that the model can accurately predict the obvious fluctuations of prices and grasp the investment opportunity. In the performance test of the investment strategy, the results show that the investment model can buy in the early stage of the bull market, hold it to rise, and accurately grasp the profit opportunities. Meanwhile, the model has the ability to survive the bear market smoothly, which means it has a high ability to resist risk fluctuations. In addition, on the basis of the given investment strategies, random disturbances are applied to generate 1000 groups of simulated investment strategies. Comparing yield of different investment strategies, we find that the 5-year average annual return of the simulated investment is lower than the investment strategy we give, and the 5-year total return of our investment strategy is higher than 93% of the simulated investment strategies, which proves that our investment model can maximize profit and minimize risk at the same time.

We test the model’s sensitivity to transaction costs. By adjusting the parameter settings of the transaction costs in the model, we find that the investment model is more sensitive to the transaction cost of bitcoin, that is, the transaction cost of bitcoin decreases by 1%, and the 5-year average annual investment rate of return increases by 1.75%. In addition, the model is more sensitive to lower transaction costs than to higher transaction costs. Finally, after multiple robustness tests, the investment model also performs well under different transaction costs, all exceeding 90% of the simulated decisions.

**Keywords**: ARIMA algorithm; NSGS-II algorithm; CVAR; downside semi-variance; multi objective programming solution

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**1 Introduction**

**1.1 Problem Restatement**

People are always looking for good investment methods to improve their asset status, and when faced with investment decisions, market traders must seek the best opportunity to invest. In order to maximize returns and diversify risks, traders often invest in multiple assets, forming a portfolio. For any investment portfolio, how to balance the two indicators of portfolio expected return and risk for asset allocation is the core problem that needs to be solved. The famous American economist Harry Markowitz systematically put forward the Portfolio Theory in 1952. On the basis of some assumptions, he established a mean-variance model of optimal asset allocation. This provides a theoretical basis for investors to find the best asset allocation ratio and achieve the best efficiency of the investment portfolio.

First, in this case, we need to develop a mathematical model for traders investing in both assets based on the past stream of daily prices of gold and bitcoin, which can provide the optimal daily portfolio investment strategy for five years. According to the idea of Portfolio Theory, we must comprehensively consider the benefits and risks, and the impact of the commission for transaction of bitcoin and gold on the investment strategy should also be taken into account.

Second, in order to build traders’ confidence in our model, we need to demonstrate in some way that the strategy provided by our model is the most effective. Then, as commission for transaction is one of the important factors affecting investment decisions, we need to find a sensitivity test method to measure the sensitivity of transaction costs to model results.

Finally, we need to provide traders with a memorandum of less than two pages showing the results of our work, including our model, the investment strategy derived from the model, and an analysis of the results.

**1.2 The Flow Chart**

The flow chart of the work in this paper is shown as follows.

Figure 1: The flow chart of our work.



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**2 Assumptions and Notations**

**2.1 Assumptions**

In order to facilitate the establishment of the optimal investment strategy model, we make the following assumptions and simplifications according to the actual situation and classical theory:

• Assuming that volatile assets such as gold and bitcoin are not allowed for short-sell transactions.

• Assuming that traders are not allowed to borrow USD during the investment process. • Assuming that the rate of return on cash is always 0.

• Assuming that traders are all risk averters. When faced with two alternatives, and other things are equal, they will choose the portfolio with less risk.

• Assuming that traders are never satisfied. When faced with two alternatives, and other things are equal, they will choose the portfolio with the higher expected rate of return.

• Assuming that gold, bitcoin and USD are infinitely divisible.

• Assuming that market information is open and transparent, and traders can obtain various information at the same time.

**2.2 Notations**

In this work, we use the nomenclature in Table 1 in the model construction. Other nonefrequent-used symbols will be introduced once they are used.

Table 1: Notations used in this literature.

Symbol Definition Unit

*gt* The price of gold on day t U.S. dollars

*Gt* The forecast price of gold on day T U.S. dollars

*bt* The price of bitcoin on day t U.S. dollars

*Bt* The forecast price of bitcoin on day T U.S. dollars

*xt* The amount of cash in the portfolio on day t U.S. dollars

*yt* Amount of gold in the portfolio on day t troy ounces

*zt* The amount of bitcoin in the portfolio on day t bitcoins

*It* The actual return of the portfolio on day t U.S. dollars

*αgold* The transaction cost rate of gold /

*αbitcoin* The transaction cost rate of bitcoin /

**3 Data processing and analysis**

**3.1 Data Pre-processing**

First of all, we observe that there are 10 missing values in the gold price data. The dates corresponding to the missing values are the working day or the previous working day on

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Christmas Eve and New Year’s Eve every year. Based on the actual situation, we consider the date on which the missing value occurs as the date when the gold market is closed. For the convenience of data analysis, we set the gold price corresponding to the date when the gold market is closed as the gold price of the previous day.

**3.2 Descriptive Statistical Analysis**

Based on the data given, we analyze the data by statistical methods and drew the following statistical graphs. It can be seen from Figure 2 and Figure 3 that the prices of gold and Bitcoin have changed greatly in the past five years, and especially the price of Bitcoin has changed more dramatically. The range for sequence {*bt*} is $62960.36 and the range for sequence {*gt*} is $941.45.

Figure 2: Time series plot of gold price sequence {*gt*}.

Figure 3: Time series plot of bitcoin price sequence {*bt*}.

Figure 4 depict the year-to-year changes in the standard deviation and Pearson correlation coefficient of gold and bitcoin prices. We can see that the standard deviation of the sequence {*bt*} is much larger than that of the sequence {*gt*} , and the absolute value of the correlation coefficient is relatively large. This shows that the price of Bitcoin fluctuates more violently, and there is a strong correlation between the price of Bitcoin and gold.

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(a) Standard deviation.



(b) Correlation coefficient.

Figure 4: Line graphs of standard deviation and correlation coefficient of sequence {*bt*} and {*gt*}.

**4 Establishment and Application of Investment StrategyModel 4.1 Predicting Asset Prices**

The Autoregressive Integrated Moving Average model is a model that analyzes the dynamic changes of time series variables based on AR and MA models, and is often used in financial data mining. The ARIMA model describes the short-term memory of sequences based on the autocorrelation of time-series data, and therefore has short-term predictive properties. According to the relevant situation of this example, after comprehensively considering various time series analysis models, we choose the ARIMA model to analyze and predict the prices of bitcoin and gold.

**4.1.1 Autoregressive Integrated Moving Average Model**

In the ARIMA( *p*, *d*, *q*) model, *d* is the number of differences made to change the time series into a stationary series, *p* is the lag order of the sequence, and *q* is the lag order of the random error term. The principle of the model is to convert the non-stationary sequence {*rt*} into a stationary sequence {*~~r~~t*} through d-order difference, and then use *~~r~~t* as the dependent variable, the lag term of *~~r~~t* and random error term *at* and the lag term of *at* as independent variables, and make a regression.

**4.1.2 Building Asset Price Forecasting Models**

1. Sequence stationary ( determine parameter *d*) :

First, we perform a stationarity test on the price series {*gt*} and {*bt*} of gold and bitcoin. It can be seen from the Figure 2, Figure 3, and Figure 5 below that the two time series have obvious trends, and the decay speed of the autocorrelation coefficient is relatively slow. At the same time, we also conduct a Unit Root Test, and there are unit roots in these two series. Therefore gt and bt are non-stationary series and need to be further differentiated.

Team # 2218743 Page 7 of 23 (a) Gold price sequence {*gt*}. (b) Bitcoin price sequence {*bt*}.

Figure 5: Autocorrelation plots of gold price sequence and bitcoin price sequence.

Let *~~g~~t* = *gt − gt−*1 and *bt* = *bt − bt−*1. After taking the first-order difference, we perform a stationarity test on {*~~g~~t*}, {*bt*}. From the Figure 6 and Figure 7 below, we can observe that the two sequences after difference always fluctuate randomly around a certain value, and there is no obvious trend. The autocorrelation coefficient decays rapidly, and only closely spaced sequences values have a significant effect. At the same time, the p-values of the unit root test are all close to 0. Thus, there is no unit root. So {*~~g~~t*} and {*bt*} are stationary sequences. Since we performed a first-order difference method to obtain a stationary series, *d* = 1.

(a) Sequence {*~~g~~t*}. (b) Sequence {*bt*}.

Figure 6: Time series plots of sequence {*~~g~~t*} and sequence {*bt*}.

(a) Sequence {*~~g~~t*}. (b) Sequence {*bt*}.

Figure 7: Autocorrelation plots of sequence {*~~g~~t*} and sequence {*bt*}.

2. Determination of order *p*, *q*:

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The ARIMA( *p*, *d*, *q*) model has the form:

*~~r~~t* = *rt − rt−*1*,*

*~~r~~t* = *φ*0 +X*p i*=1

*φi~~r~~t−i* + *at −*X*q i*=1

*θiat−i,*

where {*at*} is a white noise sequence and both *p* and *q* are non-negative integers.

The Bayesian Information Criterion (BIC) is an information criterion function that can be used to determine the optimal order of a model, and is constructed based on a Likelihood function. According to the historical data, we calculate the BIC value of the model under different orders through the computer programming loop, and find the order p and q that make the BIC the smallest, that is, the optimal order of the model. After determining the optimal order, we perform parameter estimation, and then calculate the predicted prices *Gt* and *Bt* of gold and bitcoin on day t.

3. Residual test:

In order to determine the validity of the model, a residual test is also required, in which a white noise verification is needed for the residual sequence {*a*ˆ*t*}. If the residuals are randomly and normally distributed and have no autocorrelation, it means that the residual sequence approximates a white noise sequence, indicating that the model fitting effect is great. We use the Ljung-Box statistic *Q*(*m*) to test the proximity to a white noise:

*Q*(*m*) = *T*(*T* + 2)X*m l*=1

*ρ*ˆ2*l*

*T − l.*

When the p-value of the test is greater than 0.05, it means that the residual sequence {*a*ˆ*t*} passes the test at the 5% confidence level, and the model is sufficient for modeling the dynamic linear dependence of the data.

**4.1.3 Results Analysis**

Figure 8 shows that the p-values of the residual test of the models at different times are all greater than 0.01 and most of the p-values are greater than 0.05, all of which pass the white noise test of the residuals. This is the premise that we use the ARIMA model for daily price forecasts.

(a) Gold price sequence. (b) Bitcoin price sequence.

Figure 8: Time series plots of P value of ARIMA model based on gold price sequence and bitcoin price sequence.

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Figure 9 and Figure 10 shows that the predicted price curve coincides with the actual price curve basically, the fluctuation trend remains the same, and the difference between the predicted price and the actual price is not large. Among them, the prediction accuracy is very high in the period of stable price fluctuation. In the bull and bear market period, the model can accurately predict the key turning point, but there is a certain prediction error. our forecasting model can achieve good forecasting results.



Figure 9: Time series plot of forecast gold price, actual gold price and the difference between the two.



Figure 10: Time series plot of forecast bitcoin price, actual bitcoin price and the difference between the two.

**4.2 Selecting Trading Dates Based on Market Conditions**

In this example, since there is a 1%-2% transaction commission in the process of volatile assets trading, frequent trading will increase the transaction cost, and we believe that market traders should choose the trading day more carefully. According to the different market condi tions, it can be divided into trend market and shock market. Trend market can be divided into two types: bull market (trend up) and bear market (trend down). When there is no obvious price increase or price decrease trend, that is, when the market is in a volatile market, traders should choose not to trade, considering the size of transaction costs. Traders should only trade when there is a clear upward or downward trend in the price of the volatile assets, i.e. in a bull or bear market. Using this method, we can avoid the problem of high long-term transaction costs caused by maximizing short-term returns and ignoring transaction costs when making investment decisions.

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**4.2.1 Moving Average Long Arrangement Method**

The moving average long arrangement method is a commonly used method that can effectively judge the market state. We use this method to judge the price trend, and then choose the appropriate trading day.

The principle of the moving average long arrangement method is to draw moving averages with different periods, that is, *MA*5, *MA*10, *MA*60, etc. Among them, taking *MA*5 as an example, the moving average represents the arithmetic average of the price in the last 5 days. With the appearance of a new trading day, the average array moves forward day by day, adding the price of the new trading day to the array, and removing the 6th closing price from the previous countdown. And we average the new average array, ultimately forming a moving average. When multiple moving averages show an upward trend, and the shorter the period is, the higher the position of the moving average, the volatile assets are considered to be in a bull market; on the contrary, when multiple moving averages show a downward trend, and the shorter the period is, the lower the position of the moving average, the volatile assets are considered to be in a bear market.

**4.2.2 Building Trading Day Selection Model**

When judging with the arrangement of moving averages, traders need to independently choose moving averages that cover a larger range. Given that traders are more focused on short-term gains, we set the moving averages to be more dense on shorter date ranges. Namely: 5th, 7th, 10th, 13th, 16th, 20th, 25th, 30th, 60th, 120th.

If there is a complete long arrangement of the moving averages, that is, *MA*5 *> MA*7 *> MA*10 *> MA*13 *> · · · > MA*120, and the slopes of the 10 moving averages are all positive, it indicates that the price will rise sharply and enter a bull market. However, considering that the complete long arrangement is relatively rare, we assume that when the slopes of the 8 moving averages are positive, there will be an upward price trend in the market. The moving average short arrangement is the same.

**4.2.3 Results Analysis**

Bringing in the daily prices of gold andbitcoin, the judgment results of bull market and bear market are as follows:



Figure 11: Bull and bear market judgment chart of gold price.

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Figure 12: Bull and bear market judgment chart of bitcoin price.

Figure 11 and Figure 12 show that the bull and bear market distributions of gold and Bitcoin are inconsistent, that is, the buying and selling nodes of volatile assets are different. The discontinuity indicates that the market does not present an obvious buying and selling opportunity, and market traders will not have trading behavior. Based on the results, we get indicators describing the state of the gold and bitcoin markets: *Mt* and *Nt*.

(

*Mt* =

(

*Nt* =

1 The gold market is in a bull or bear market. 0 Others.

1 The bitcoin market is in a bull or bear market. 0 Others.

Then when *Mt* = 0, our investment decision should not conduct gold transactions, and similarly when *Nt* = 0, we should not conduct bitcoin transactions.

**4.3 Measuring the Risk of Portfolio**

In order to make the best investment decisions, we must consider the risk of our asset portfolio. Choosing an appropriate method to measure portfolio risk is the key.Considering that the use of variance and *β* coefficient to measure risk is not intuitive, and it only reflects the volatility of the market (or assets), we choose to use the CVaR method to measure the risk of the portfolio, which is a risk measurement method based on VaR.

**4.3.1 Conditional Value at Risk (CVaR)**

The VaR method is used to estimate the worst loss condition of the assets held under a given confidence level, that is, the maximum loss value. Since VaR cannot satisfy sub-additivity in asset diversification and the measurement of tail losses is not sufficient, Uryasev and Rockafellar further proposed a conditional value-at-risk (CVaR) to overcome these defects. CVaR measures the average loss value of the investment portfolio under the condition that the loss exceeds a given VaR value, which can improve the intuitive impression for traders, and is also in line with the worst-case expectations that traders assign to assets when making transactions. At the same time, it not only satisfies the properties of consistent risk measurement, but also has good

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properties such as convexity.Under the assumption that returns *r* follow a normal distribution, the formula for calculating CVaR is as follow:

2*}**σ*(*r*) *− E*(*r*)*,*

*~~√~~*2*πexp{*[*φ−*1(*α*)]2

1

*CV aR* = *C*(*α*)*σ*(*r*) *− E*(*r*) = 1 1 *− α*

where *α* is the significance level, *E*(*r*) is the expected value of *r* and *σ* is the standard deviation of *r*.

**4.4 Finding the Best Investment Strategy**

In order to get the optimal investment strategies, we need to comprehensively consider the returns and risks of the asset portfolio. In order to achieve the decision goals of maximizing returns and minimizing risks at the same time, we build a model for trading strategy based on the multi-objective NSGA-II algorithm, and calculate the feasible solution set of the daily asset portfolio. Ultimately, we take into account the risk aversion of market traders and use the limitation of downside semi-variance to obtain the final daily trading strategy. By iterating through a day-by-day loop, we end up with daily transactions for five years.

**4.4.1 Establishment of Optimization 0bjective Functions and Constraints**

Due to the premise that traders are all risk averter, when traders make strategic decisions, they pursue profit maximization and their trading decisions are limited by risks. Therefore, we set two objective functions.

1. The first objective function: Maximum of expected investment profit (*I*e*t*):

It is known that the asset allocation held on day t-1 is [*xt−*1*, yt−*1*, zt−*1], the prices of gold and bitcoin are *gt−*1, *bt−*1 respectively. And the asset allocation held on day t is [*xt, yt, zt*], and the predicted prices of gold and bitcoin are *Gt*, *Bt*. Among them, [*xt, yt, zt*] are optimization parameters.

Thus, the traders’s expected profit *I*e*t* can be expressed as:

*I*e*t* = *−*1%*|yt − yt−*1*|Gt −* 2%*|zt − zt−*1*|Bt* + (*Gt − gt−*1)*yt* + (*Bt − bt−*1)*zt.*

2. The second objective function: Minimum of investment risk (CVaR): First, we define the weight vector of asset portfolio as:

*Wt* = (*w*1*,t, w*2*,t, w*3*,t*)*T,*

*w*1*,t* =*xt*

*xt* + *ytGt* + *ztBt, w*2*,t* =*ytGt*

*xt* + *ytGt* + *ztBt, w*3*,t* =*ztBt*

*xt* + *ytGt* + *ztBt.*

Next, we define vector *µt* as:

*µt* = (*µ*1*,t, µ*2*,t, µ*3*,t*)*T,*

*µi,t* =*ri,*1 + *ri,*2 + *· · ·* + *ri,t−*1

*t −* 1*.*

The, we define the matrix *Ct* as:

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*Ct* =

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*σ*21*,t σ*212*,t σ*213*,t σ*221*,t σ*22*,t σ*223*,t σ*231*,t σ*23*,t σ*233*,t*



 *,*

*σ*2*i,t* =1 *t −* 2

X *t−*1

*k*=1

(*ri,k − µi,t*)*, σ*2*ij,t* = *σi,tσj,tρij .*

In the above formulas, *ri,t* is the actual rate of return of asset i, *σ*2*i,t* is the variance of the rate of return of asset i, and *σ*2*ij,t* is the covariance of the rate of return of asset i and the rate of return of asset i.

Therefore, combined with the definition of CVaR, we can express the CVaR of asset portfolio: q

*CV aR* = *C*(*α*)

*C*(*α*) = 1

1 *− α*

3. Constraint functions:

*WTt CtWt −* (*WTt µt*)*,* 2*}**.*

*~~√~~*2*πexp{*[*φ−*1(*α*)]2 1

In particular, in the bull and bear market judgment model, we get the data*Mt*, *Nt* representing the market state. When the gold price is in a bull or bear market, we choose to trade gold; otherwise, we do not trade gold and keep our gold holdings. The same is true for the bitcoin price. The specific performance is as follow:

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*yt* = *yt, zt* = *zt Mt* = 1*, Nt* = 1 *yt* = *yt, zt* = *zt−*1 *Mt* = 1*, Nt* = 0 *.*

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*yt* = *yt−*1*, zt* = *zt Mt* = 0*, Nt* = 1 *yt* = *yt−*1*, zt* = *zt−*1 *Mt* = 0*, Nt* = 0

At the same time, since there is no short-selling behavior in volatile assets, the holdings of gold and bitcoin in asset allocation are required to be no less than 0. In addition, we set that traders can only invest with the initial $1,000 and do not allow borrowing for daily transaction, that is, the cash held after each transaction is not less than 0. Thus, the optimization parameters are constrained as follows:

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*xt* = *xt−*1 *−* 1%*|yt − yt−*1*|Gt −* 2%*|zt − zt−*1*|Bt −* (*yt − yt−*1)*Gt −* (*zt − zt−*1)*Bt ≥* 0 *.*

*yt ≥* 0



*zt ≥* 0

**4.4.2 Principle of NSGA-II Algorithm**

The NSGA-II algorithm, a fast non-dominated multi-objective optimization algorithm with an elite retention strategy, is a multi-objective optimization algorithm based on the Pareto optimal solution. Because the algorithm can achieve multiple objectives, and can perform great in both

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the diversity and convergence of the solution set distribution, we choose this algorithm to solve the problem. The specific implementation process is as follows:

**(1)** Randomly generate the initialized population of individuals, judge the hierarchical ordering of all individuals, and perform non-dominant ordering on unfinished individuals.

Among them, the dominance relationship refers to the Pareto dominance relationship: For the minimization multi-objective optimization problem, for *n* objective components *fi*(*x*),*i* = 1*,* 2*, · · · , n*, two decision variables *Xa*, *Xb* are given arbitrarily, if the following two conditions are true, then *Xa* dominates *Xb*.

1. *∀i ∈* 1*,* 2*, · · · , n, fi*(*Xa*) *≤ fi*(*Xb*)

2. *∃i ∈* 1*,* 2*, · · · , n, s.t. fi*(*Xa*) *< fi*(*Xb*)

**(2)** The genetic operations of selection, crossover, and mutation are performed on the parent population, and the individual genes are genetically recombined into new individuals to generate the offspring population.

**(3)**Combine the parent population and the offspring population to generate a new population, quickly sort the new population non-dominated, calculate the crowding distance of each indi vidual on non-dominated layer, and select the best individual to form a new parent population. Among them, the smaller the crowding distance of individuals, the denser the non-dominated individuals, and the poorer the diversity of individuals. Thus, they are eliminated.

**(4)** Algorithm iterates from this, and when the number of iterations reaches the expected setting, it terminates.

**4.4.3 Building Investment Decision Model**

According to objective function and constraint conditions, we first use NSGA-II algorithm to achieve multi-objective programming solution, and obtain feasible solution set. As the expected return increases, the conditional value at risk (CVaR) increases. To further our final decision, we use the downside semi-variance limitations to make the final decision based on the feasible set. Considering the fact that investors believe that situations where actual returns are higher than average returns cannot be included in the investment risk, Markowitz proposed the method of the downside semi-variance, which solves the problem of different investors’ preference structures to a certain extent. We believe that investors have an upper limit on their acceptance of the risk of falling returns, but there is no upper limit on their acceptance of the risk of rising returns. Therefore, we use the downside semi-variance model to optimize the risk measure to limit the risk of falling portfolio returns and get the optimal investment portfolio based on the model.

Therefore, we bring the corresponding asset allocation [*xt, yt, zt*] in the feasible solution into the downside semi-variance model, and solve the downside semi-variance *V* .

*V* = *WT C−WT.*

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*σ*2*−*

1*,t σ*2*−*

12*,t σ*2*−*

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

*σ*2*−*

21*,t σ*2*−*

13*,t*

 *.*

*C−* =

*σ*2*−*

2*,t σ*2*−* 23*,t*

31*,t σ*2*−*

3*,t σ*2*−*

33*,t*

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*σ*2*−*

*i,t* =

*σ*2+

*i,t* =

(

(*ri,t − µi,t*)2(*ri,t − µi,t*) *≤* 0 0 (*ri,t − µi,t*) *>* 0*.*

(

(*ri,t − µi,t*)2(*ri,t − µi,t*) *>* 0 0 (*ri,t − µi,t*) *≤* 0*.*

*i,t σ*2+

*i,t σ*2*−*

*ij,t* =*σ*2*−*

2 +*σ*2+

*j,t* +*σ*2*−*

*σ*2*−*

*i,t σ*2*−*

*j,t*

*j,t*

2

*σ*2*i,tσ*2*j,tσij,t.*

We sort the solved downside semi-variance from smallest to largest, set the 70% quantile as the daily risk limit, and take asset portfolio under the risk limit as the best investment strategy. That means, under the condition of constraining the upper limit of risk, we select the asset allocation with the largest investment return, and then proceed to the next iterative loop solution based on the solution.

**4.4.4 Results Analysis**

Figure 13 depicts daily gold and bitcoin holdings (measured in U.S. dollars) based on an investment strategy based on our model. We can see that This strategy comprehensively considers the characteristics of bitcoin and gold, and chooses to buy a lot when bitcoin is at a low level, reducing the proportion of gold assets. When the downside risk of bitcoin increases, choose to hold a large amount of gold to hedge the risk, and when the risk of both assets is high, choose to hold more cash, so as to reduce the risk while maintaining a larger return. For example, in the bitcoin bull market from 2020 to 2021, the proportion of bitcoin assets is much larger than that of gold. In the bear market, the proportion of gold assets will increase rapidly to reduce risks. The cumulative return rate of the investment strategy given by this model during 2016-2021 is shown in Figure 14. According to the final investment decision, the total assets will reach $617,643.2 after five years, and the average annual rate of return will reach 261.41% within five years. Among them, the annual yield in the second year is the largest, which is 664.69%.

Figure 13: Time series plot of gold and bitcoin holdings (measured in U.S. dollars).

Team # 2218743 Page 16 of 23 Figure 14: Time series plot of cumulative return (%) from 2016 to 2021

**5 Investment Strategy Optimality Test**

In order to prove that the strategy provided by our model is the optimal strategy, we will analyze and prove it from the perspectives of prediction accuracy and strategy effectiveness.

**5.1 Prediction Accuracy Test of Model**

In terms of prediction accuracy, we use five common indicators to evaluate the prediction results of ARIMA to analyze the deviation between the predicted value of volatile assets’ price and the real value. The MSE, RMSE, MAE, MAPE and R2-score results calculated by python are shown in the Table 2 below.

Table 2: Prediction error evaluation index results.

Assets MSE RMSE MAE MAPE R2-score

Gold 395.8478 19.8959 13.6976 0.009 0.9486

Bitcoin 1205107.406 1097.7738 542.9281 0.0402 0.9486

The prediction results for gold and bitcoin price show that the MAPE values are both less than 0.1, which are extremely close to 0%, indicating that the model is close to perfect. R2-score values are greater than 94%, which are close to 1, reflecting that all the variance of the predicted value can be explained by the actual value. This shows that the model can accurately predict the moment when the market price fluctuates greatly, thus providing a good precondition for us to make subsequent investment strategies.

**5.2 Effectiveness Test of Investment Strategies**

In terms of the effectiveness of investment strategies, we use the method of analyzing critical period of investment and the method of applying random interference to test and analyze.

**5.2.1 Analyzing Critical Period of Investment**

First, taking the period from November 2020 to April 14, 2021 as an example, Bitcoin was in a bull market with an increase of 360.2%. According to the investment strategy we gave, buy gold in the early stage of the bull market and hold it to rise. During this period, the total investment return rate reached 314.3%, and the profitability was high, which made a good grasp of the

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profit opportunities brought by this opportunity.

(a) Bull market ( 2020.11-2021.4). (b) Bear market ( 2021.4-2021.7).

Figure 15: Time series plots of cumulative returns in a bull market ( 2020.11-2021.4) and a bear market ( 2021.4-2021.7).

From April 15, 2021 to July 2021, bitcoin was in a bear market and its prices fell sharply. We can accurately predict the coming of the bear market and make quick decisions to sell bitcoin and hold more gold and cash. Consequently, the total rate of return on investment during this period has been maintained at -3%. After testing, our investment model has the ability to survive the period of bear market smoothly, has a high ability to resist risk fluctuations, and can keep asset losses to a minimum.

**5.2.2 Random Interference Method**

The random interference method is based on the our optimal investment strategy, and applies stochastic disturbance to the gold, bitcoin and cash holdings of each day in five years, generating M groups of new simulated investment strategies. Then, we compare the M groups of investment strategies with actual investment strategies in the five-year total return and the annual return for each year. The holding amount after random disturbance is set as a random number within 10% of the gold holding amount and the bitcoin holding amount, and the cash holding amount is determined according to the gold holding amount and the bitcoin holding amount after the disturbance. Also, it is necessary to ensure that the cash holdings >0.

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(1 *−* 10%)*yt < yt* + *εt <* (1 + 10%)*yt*

*.*

(1 *−* 10%)*zt < zt* + *εt <* (1 + 10%)*zt*

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*xt* = *xt−*1 *−* 1%*|yt − yt−*1*|Gt −* 2%*|zt − zt−*1*|Bt −* (*yt − yt−*1)*Gt −* (*zt − zt−*1)*Bt ≥* 0

From Table 3, the average annual rate of return on simulated investment is lower than that of actual investment, and the average total rate of return within 5 years is lower by 20.96%. At the same time, only 7% of the simulated investment strategies have a 5-year total return higher than the actual investment strategies we give. The result indicates that our investment model has a good performance in the five-year period when the macroeconomic environment is constantly changing and financial market risks are high, especially in market tracking ability, anti-risk ability, and earning ability.

**6 Sensitivity Analysis of Investment Model**

Taking into account the changes in the macroeconomic environment from 2016 to 2021, the huge fluctuations in the capital market and the subsequent changes in US trading regulations, we

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Table 3: Comparison of the rate of return of new simulated investment and that of actual investment.

*I*1*st year I*2*nd year I*3*rd year I*4*th year I*5*th year I*1*−*5 *year*

Actual investment 368.99% 664.69% 102.48% 55.60% 453.03% 261.41% Simulated investment 328.65% 610.85% 91.53% 49.61% 422.62% 240.45%

will conduct a targeted sensitivity analysis on the transaction cost parameters in the investment model to prove that the investment model can make corresponding adjustments to random financial events and provide the optimal investment strategy.

**6.1 Market Risk Analysis**

From the overall analysis of the U.S. capital market, in November 2016, Trump was unex pectedly elected, the dollar rose sharply, technology stocks and financial stocks reversed, and the Federal Reserve raised interest rates by 25 basis points in December, which further promoted the dollar index to rise. At the end of 2017, the tax reform bill was passed, and the scope of influence gradually expanded from the bond market to the stock market, from the international market to the US stock market, from growth stocks to value stocks, and the S&P 500 index continued to rise. In 2018, under the combined influence of Sino-US trade frictions, the US mid-term elections and other factors, both the Nasdaq and the S&P entered a "technical bear market". In 2019, the U.S. 3-month and 10-year treasury yield curve inverted, which once triggered panic in the European and American markets and caused shocks in the global market. In 2020, affected by the COVID-19 epidemic and the US election, investors have chosen to adjust their asset allocation and prefer low-risk assets. In addition, the deterioration of the US epidemic in 2021 will once again increase the risk of the stock market. Therefore, changes in the global financial and economic environment, domestic macro-politics, and economic environment will all have a greater impact on the stock market. Then, the U.S. stock market will choose to change the cost of transaction to alleviate the impact on stock price trends.

Specifically, from the analysis of the gold market, the random short-term or long-short game will cause short-term fluctuations in the gold price, and the mid-line market is determined by regional conflicts and geopolitics, which are difficult to predict. In the long run, the dollar shows a depreciating trend, which continues to push up the price of gold. In the bitcoin market, the relationship between supply and demand greatly affects the price of bitcoin. The negative price elasticity of demand allows the price of the bitcoin to continue to rise when it is high, but it also brings a huge risk of falling prices.

On the whole, there have been many changes in the international and domestic environment during the five years from 2016 to 2021, then transmitting to the stock market, which is specifically reflected in transaction costs. When the stock market is booming, transaction costs tend to increase, so it is important to examine the sensitivity of investment models to changes in transaction costs.

**6.2 Sensitivity Analysis and Robustness Test**

**6.2.1 Sensitivity Analysis**

By increasing or decreasing the percentage of transaction cost, we adjust the transaction cost of bitcoin to 1%, 2%, and 3%, and the transaction cost of gold to 0.5%, 1%, and 1.5% respectively,

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run the investment model again under different transaction costs. Finally, we analyze the results of strategy model and the range of changes in assets portfolio. The results are shown in the Table 4.

Table 4: Annual rate of return on investment under different transaction costs. Transaction Costs *I*1*st year I*2*nd year I*3*rd year I*4*th year I*5*th year I*1*−*5 *year*

*αbitcoin*=1%,*αgold*=0.5% 371.92% 712.55% 97.77% 57.37% 442.04% 263.93% *αbitcoin*=1%,*αgold*=1% 370.39% 710.64% 97.85% 56.36% 442.61% 263.16% *αbitcoin*=1%,*αgold*=1.5% 368.86% 708.71% 97.92% 55.33% 443.20% 262.37% *αbitcoin*=2%,*αgold*=0.5% 370.52% 666.76% 102.37% 56.66% 452.31% 262.20% *αbitcoin*=2%,*αgold*=1% 368.99% 664.69% 102.48% 55.60% 453.03% 261.41% *αbitcoin*=2%,*αgold*=1.5% 367.46% 662.60% 102.59% 54.54% 453.77% 260.62% *αbitcoin*=3%,*αgold*=0.5% 369.12% 620.69% 107.59% 55.89% 463.51% 260.44% *αbitcoin*=3%,*αgold*=1% 367.59% 618.46% 107.73% 54.79% 464.40% 259.63% *αbitcoin*=3%,*αgold*=1.5% 367.46% 662.60% 102.59% 54.54% 453.76% 260.61%

Obviously, when the transaction cost decreases, the annual rate of return increases, and the results of the investment model are more sensitive to the transaction cost of bitcoin. To be specific, when the transaction cost of bitcoin remains unchanged, the transaction cost of gold decreases by 0.5%, and the 5-year total rate of return increases by 0.79%. When the transaction cost of gold is unchanged, the transaction cost of bitcoin decreases by 1%, and the total 5-year return increases by 1.75%. In addition, when transaction costs rise, the annual rate of return falls, but its impact is smaller than the impact of lower transaction costs.The results are shown in the Table 5.

Table 5: Ranking of actual investment model performance under different transaction costs. Transaction Costs Rank

*αbitcoin* = 1%*, αgold* = 1% 78

*αbitcoin* = 1%*, αgold* = 0*.*5% 66

*αbitcoin* = 1%*, αgold* = 1*.*5% 43

*αbitcoin* = 2%*, αgold* = 0*.*5% 6

*αbitcoin* = 2%*, αgold* = 1*.*5% 10

*αbitcoin* = 3%*, αgold* = 0*.*5% 17

*αbitcoin* = 3%*, αgold* = 1% 25

*αbitcoin* = 3%*, αgold* = 1*.*5% 56

The performance rankings of the investment models are all in the top 10%, indicating that our models also perform well under different transaction costs and are worthy of trust.

**6.2.2 Robustness Test**

After changing the transaction cost, we use the random interference method above to test the robustness of the model, thus proving that the investment model can still provide a relatively profitable investment strategy under the perturbation of the transaction cost parameter. Specif ically, we apply 1000 random disturbances to the eight models respectively, obtain the annual returns and 5-year total returns of the actual model and the model after disturbance, and give the ranking of our actual investment strategy among the investment strategies after disturbance.

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**7 Model Evaluation**

**7.1 Strengths**

• The investment strategy model integrates the knowledge of economics and finance, and the establishment of model is based on Markowitz’s mean-variance theory and CVAR theory, with strong reliability. In addition, the trading day judgment model is based on the moving average long arrangement method, which has passed sufficient historical tests and is highly credible.

• The investment strategy model is applicable to a wide range of objects, and can adjust the corresponding risk upper limit according to the different anti-risk capabilities of traders, thereby providing targeted and optimal investment strategies.

• According to the results of the optimal investment strategy test and sensitivity analysis of the model, it is proved that our model can adapt to different economic environments and provide the best profitable investment strategy, ensuring that the risk is minimized at the same time.

**7.2 Weaknesses**

• Due to the limitation of the CVAR model, the investment strategy is based on the as sumption that the return on assets obeys the normal distribution. Thus, the data of other distribution types needs to choose another model to obtain optimal strategies. Because of the limited data, our investment strategy model is only tested on a set of 5-year asset price data, and the scope of application of the model remains to be determined.

• There are too many calculation items, which is relatively cumbersome, and the running speed of the model needs to be improved.

**Memorandum**

**To:** traders

**From:** Model Development Team

**Subject:** An introduction to investment strategy models

**Date:** February 22, 2022

This memo introduces our investment strategy model for you from four perspectives: the establishment of transaction strategy model, the robustness of the model, the sensitivity of the model, and investment returns.

1. Establishment of transaction strategy model.

It is common sense that accurately predicting the future trend of asset prices is the basic premise of correct investment decisions. We use the ARIMA model commonly used in time series analysis to determine reasonable model parameters based on known historical data to predict the next day’s price. Because too frequent trading will increase transaction costs and bring greater investment risks , we clarify the current market state and judge whether to trade at present based on the moving average long arrangement method. Finally, we established a revenue-CVAR dual-objective optimization model and obtained a series of feasible solutions through the NSGA-II algorithm, and then the daily trading strategy is obtained by combining the upper limit of the downside semi-variance of the asset portfolio. At the same time, our model can modify the upper limit of the risk constraint according to the investor’s degree of risk aversion, and obtain the best investment strategy that matches anyone’s risk tolerance.

Figure 16: Establishment of transaction strategy model.

2. Robustness of the model.

In the prediction bias test, the MAPE values are all less than 0.1, very close to 0. R2-score values are all greater than 94%, close to 1, indicating that the model can accurately predict the key moment when the asset price fluctuates greatly, thus providing a good precondition for subsequent investment decisions.

After the investment strategy optimality test, our investment model can buy assets before the bull market, hold to rise, and accurately grasp the profit opportunities. At the same time, the model has the ability to survive the period of bear market smoothly, with high anti-risk fluctuation ability, and can keep the asset loss to a minimum in the bear market.

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In addition, we apply random disturbance to the given investment strategies to generate 1000 groups of new simulated investment strategies. The comparison of returns shows that the average annual returns of simulated investments are lower than the investment strategies given by us, and the 5-year total returns of our investment strategies are higher than 93% of the simulated investment strategies, which is enough to prove that our investment model can provide you with a relatively profitable investment strategy while minimizing risk.

3. Model sensitivity.

Since changes in the global financial and economic environment, domestic macro-politics, and economic environment will all have an impact on the market, the volatile assets transaction costs are likely to change accordingly. By adjusting the parameter settings of transaction costs, we find that our investment model is more sensitive to the transaction cost of bitcoin, and the model is more sensitive to the reduction of transaction cost relative to the increase of transaction cost. At the same time, after multiple robustness tests, our investment model also has good performance under different transaction costs, exceeding 90% of the simulated decisions, which is worthy of trust.

4. Investment return.

The 5-year total rate of return on the investment reaches 616.63%, the average annual rate of return is 261.41%, and the highest annual rate of return is 664.68%, which means our model has strong profitability. The lowest annual rate of return is 55.6%, which means that the model can quickly adjust asset allocation and has strong anti-risk capabilities.

Should you need more information, we’ll be glad to introduce more about the Investment Strategy Model.

From 2016 to 2018, the market performance was relatively stable and the risk was small. We are optimistic about the rise of bitcoin, choose to hold a large share of bitcoin with a relatively low valuation and hold a certain amount of gold to hedge risks, which accurately predict and grasp the upward trend of bitcoin. The three-year returns were 368.99%, 664.68%, and 102.48%.

In 2019-2021, the market performance was volatile, and bull and bear markets appeared frequently. In 2020, we accurately grasped the opportunities in the bitcoin market, buy at low prices, and achieve an annual return of 55%. In 2021, we will seize the opportunity to reduce bitcoin holdings and buy gold to take profit before the bear market comes. The yield in 2021 is 453.03%, finally achieved a 5-year cumulative growth of 616.63%.

Therefore, our investment strategy model can grasp the reasonable relationship between investment opportunities and trading volume, and have the ability to stop loss and take profit for the purpose of effectively avoiding risks, recommending profitable investment strategies that best suit your risk-resisting ability.

The above is the whole content of our model. Should you need more information, we’ll be glad to discuss our investment strategy models in detail at next meeting.

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**Problem Chosen** C

**2022**

**MCM/ICM**

**Summary Sheet**

**Team Control Number** 2218931

**Finding the Best Strategy with Quantitative Models**

**Summary**

Market traders seek to maximize returns through frequent buying and selling activities. However, financial markets are complex and volatile, and it is not easy to achieve their goals by relying only on experience to determine trading strategies. Quantitative trading methods make the path to return precise and reliable by building a reasonable model.

We constructed model I: **LM-BP Neural Network Model** and model II: **Recurrent Decision Model**. The two models are closely linked and constitute the final Quantitative Trading Decision Model, which is used to help traders determine the best decisions for a portfolio consisting of cash, gold, and bitcoin.

For model I: We use the **Levenberg-Marquardt algorithm** based on numerical optimization to improve the traditional BP neural network. The model uses valid historical price data for seven days to make long-term and short-term price forecasts. Subject to trading rules, the long-term forecast for gold is five days after the day; the long-term forecast for Bitcoin is seven days after the day. Both short-term forecasts are for the next day. We tested the model with historical price data, and its *R*2exceeded 0.99, and the predictions worked well.

For model II: The core idea of the circular decision model is to execute a "buy low, sell high" strategy based on the future price trend of an investment product. It consists of four stages: "Stand by", buy, hold and sell. No decisions are made for the first ten days to accumulate historical price data; buy them if there is an uptrend in the short or long term and reach a threshold. Threshold settings are related to transaction costs and expected returns. **The short-term and long-term thresholds are 2% and 3% for gold and 3.5% and 4.5% for Bitcoin.** We use the *Sharpe ratio* to measure the riskiness of a portfolio and use it to determine the purchase share of each product in the portfolio. Sell them if both short-term and long-term forecast price declines. Account funds should be updated after each transaction is completed.

We can draw the following conclusions after model solving, model checking, and sensitivity analysis. We input historical price data into quantitative investment decision-making models for simulated trading for problem one. The initial capital is $1,000, and after a five-year trading period, **the asset value is $270,836**. For problem two, the evidence that we make the best decisions is that the model’s parameters have been optimized; the investment returns are also higher than simple long-term trading, short-term trading, and some high-performance investment companies. For problem three,we find that both the trading strategy and the trading results are susceptible to the Bitcoin commission payment ratio change and less sensitive to the gold commission payment ratio change.

Finally, we wrote a memo for the trader with our models, strategies, and results. Moreover, the advantages and disadvantages of the model are analyzed.

**Keywords**: LM-BP long and short term forecast circular decision quantitative investment

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**1 Introduction**

**1.1 Problem Background**

*"Looking at the prices, I can see something we can study here, maybe a way to predict, mathemat ically or statistically. So I built some models, and models got better and better. Finally, the modal replaced the fundamental stuff."*

*—James Simons,the King of Quants*

With the continuous development of deep learning and artificial intelligence, quantitative trading strategies have gradually become mature and accepted by traders.Quantitative trading has gradually emerged since the 1970s. Sharpe’s Capital Asset Pricing Model and Ross’s Arbitrage Pricing Theory have promoted its prosperity extensively. Although the impact of the financial crisis has not been avoided and there are still model failures, quantitative investment is still necessary and practical. After all, the Medallion Fund operated by Simons has an average annual return of 35%!

Compared with traditional investment methods that rely on investment experience or analysis of financial data, establishing a suitable forecasting model based on the historical price data of the investment object and quantifying the decision-making method of an effective trading strategy can help traders make trading decisions more conveniently while obtaining higher returns.

**1.2 Restatement of the Problem**

Through in-depth analysis and research on the background of the problem, combined with topic specific constraints and requirements given, the restate of the problem can be expressed as follows:

• Develop a Quantitative Trading Decision Model based on the historical price data of gold and bitcoin over the past five years, constrained by trading rules and providing the best daily trading strategy. Note that the model can only be built using the given price data on and before the trading day. That is, when making daily trading strategies, we do not know the future prices of gold and bitcoin.

• Beginning on September 11, 2016, traders used an initial capital of $1,000 to adjust the investment portfolio consisting of U.S. dollars, troy ounces, and bitcoins according to the decisions given by the Quantitative Trading Decision Model and calculate the investment income after a five-year trading period.

• Present evidence that the parameters in the established model are optimal, and the obtained strategy is the optimal strategy of the model. Prove that our strategy can achieve higher returns than other strategies.

• Considering the results obtained above, prepare one to two pages of memorandum to com municate the model and strategy to the trader.

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**1.3 Literature Review**

In order to determine the best daily trading strategy, the prices of gold and Bitcoin can be predicted step by step and then combined with the existing investment portfolio strategies to determine the appropriate trading method and establish a quantitative trading decision-making model. The relevant research of the following scholars is for us Provides ideas:

• The price of gold has the characteristics of dynamic, nonlinear and time-varying. The prediction of the gold price by traditional methods relies on the linear relationship between its prices, which has obvious limitations and low prediction accuracy. Zeng Lian et al. (2010) [1]and Zhang Jundong et al. (2010) [2]used an improved neural network model to achieve high-precision simulation of gold price forecasting. Lin Yu et al. (2010) [3] and Jing Zhigang and Shi Guoliang (2017) [4]adopted an improved ARIMA model, which has higher prediction accuracy than a single prediction model. In recent years, the price prediction model based on LSTM has attracted the attention of scholars. Yuan Dongfang (2021) [5] predicted the price of gold futures based on the CEEMDAN-PCA-LSTM model.

• Muzammal(2019) [6] found that bitcoin prices are highly volatile, and Wong’s(2014) [7] economic analysis shows that the returns are incredibly high. Katsiampa(2017), Selin(2020), Duan(2020) [8–10] forecast Bitcoin price and volatility using traditional time series fore casting methods. Compared with traditional linear statistical models, artificial intelligence methods can better capture the high volatility of Bitcoin prices. Marendra(2018) [11] com pared the ARIMA model with the LSTM deep learning model and found that the mean absolute error of the LSTM model was significantly lower. Ciaian(2016) [12] further com pared the deep learning model, the autoregressive ensemble model, and the ARIMA model and concluded that the deep learning model performed better in classification prediction.

• Quantitative trading relies on computers to configure investment portfolios, which is more scientific and rational than traditional trading decisions. Its quantitative models can be roughly divided into two categories. One is the model based on statistical theory. For example, Zhang Peng (2008) [13]studied the mean-variance and mean-VaR portfolio models when short selling is not allowed and verified the algorithm’s effectiveness through empirical research. The other category relies on the development of artificial intelligence technology, such as trading algorithms based on deep reinforcement learning. Xiong Lidong (2019) [14] and Fan Xiaoyu (2021) [15] studied it. They found that the strategy does not rely on complex expert experience, nor does it need to make explicit predictions about the market environment, and can directly output trading strategies its effectiveness.

To more intuitively reflect the research situation of scholars in the field of quantitative trading, we draw Figure 1 based on the content of the literature review.

Team # 2218931 Page 5 of 25 Figure 1: Literature Review Framework of Model

**1.4 Our Work**

The problem requires building a quantitative trading decision model to achieve the best trading strategy. Our work mainly includes the following:

1) Based on the price data of gold and bitcoin, the LM-BP Neural Network Model is constructed. Use the model’s output of the predicted price to build a Recurrent Decision Model. The two constitute a Quantitative Trading Decision Model together, providing the best daily trading strategy.

2) We prove that our strategy is optimal by optimizing parameters and setting a control group.

3) Change the commission ratio for gold and bitcoin, and analyze the impact of transaction costs on strategies and results.

4) Wrote a memo for traders with our models, strategies and results.

In order to avoid complicated description, intuitively reflect our work process, the flow chart is shown in Figure 2:

Team # 2218931 Page 6 of 25 Figure 2: Flow Chart of Our Work

**2 Assumptions and Explanations**

In reality, financial markets operate in complex situations, we need to make reasonable assumptions to simplify the model, and each hypothesis is closely followed by its corresponding explanation:

• **Assumption 1: The amount of funds traded is small enough not to affect the behavior of other traders in the market and the price of financial assets.**

*,→* **Explanation:**Larger transaction capital volumes may impact market prices, resulting in transaction costs not necessarily proportional to transaction value.

• **Assumption 2: Regardless of the price fluctuations of gold and bitcoin on the day, the given data is used as the day’s trading price.**

*,→***Explanation:**The price of gold and bitcoin is volatile at different times of the day, so their prices are not volatile. However, considering that the trading period is long and only a given daily historical price can be used, we make this assumption.

• **Assumption 3:Traders can purchase any amount of Bitcoin and Gold according to the optimal allocation of funds, and the purchase amount can be a non-integer number.**

*,→* **Explanation:**Traders rarely use all their funds to buy gold or bitcoin in reality, and the number of transactions is usually a whole number. In order to find the optimal combination strategy, we allow exceptional cases to occur.

• **Assumption 4:Only consider trading strategies where a short sale is not allowed.**

*,→* **Explanation:**Allowing short sale increases the risk for traders and financial markets, and our goal is to maximize returns with as little risk as possible.

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Additional assumptions are made to simplify analysis for individual sections. These assump tions will be discussed at the appropriate locations.

**3 Notations**

Table 1 shows the necessary notations and signs used in this paper. Other notations and signs will be declaired or defined when using.

Table 1: Notions and Symbol Description

Symbols Description

*Hj* The hidden layer output of the neural network

*Ok* The output of the output layer of the neural network

*Wij* The weights from the input layer to the hidden layer

*Wjk* The weights from the hidden layer to the output layer

*aj* Thresholding in the hidden layer of a neural network

*f* An assumed functional relation which maps a parameter vector *t* Assume buying gold or bitcoin on day *t*

*t′* Assume selling gold or bitcoin on day *t′*

*α*1*,*2 Short-term predicted price increase threshold for gold or bitcoin *β*1*,*2 Long-term predicted price increase threshold for gold or bitcoin

**4 Quantitative Trading Decision Model**

Traders decide the day’s portfolio investment strategy according to the prices of gold and bitcoin. In order to obtain the best investment returns, they need to have a reasonable and accurate estimate of the future price trends and fluctuations of the two and then follow a certain trading strategy to make today’s investment decisions. Therefore, the Quantitative Trading Decision Model to be established include two steps: first, construct a high-precision prediction model, and then quantitative modeling of the investment strategy is carried out, and finally, realize the purpose of automatic quantitative trading decision-making.

**4.1 Price Prediction Model Based on LM-BP Neural Network**

In recent years, due to the good nonlinear characteristics, flexible and effective learning methods, and strong anti-interference ability of the BP neural network, it has been widely used in forecasting research. We consider using neural network methods to predict their prices by combining the prediction models in the literature review and the dynamic, nonlinear, and volatility characteristics of gold and bitcoin prices.

When the traditional BP algorithm based on the standard gradient descent method solves practical problems, the quality of the solution is often affected because the convergence speed is too slow. Therefore, many improved training algorithms based on nonlinear optimization have been proposed to improve the convergence speed of network training. The improved algorithms can be divided into two categories:

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• **Improvement methods based on standard gradient descent.** Including BP algorithm with additional momentum, BP algorithm with variable learning rate, and elastic BP algorithm. Such improved algorithms are primarily applied to simple problems.

• **Network training algorithms based on numerical optimization methods.** Including quasi Newton method, Levenberg-Marquardt method (after this referred to as LM), and conjugate gradient method. Use the first and second derivative information of the objective function at the same time. It is a better choice for complex practical problems.

Since the price trends of gold and bitcoin are complex and the amount of data is large, the numerical optimization method is more suitable for improving the BP neural network. Zhou Kaili and Kang Yaohong (2005) [16] designed a MATLAB simulation program. They found that the LM algorithm has the fastest convergence speed and higher computational accuracy for small and medium-sized neural networks. Given the advantages of the above LM algorithm, this section uses the LM-BP neural network algorithm to predict the price of gold and bitcoin.

**4.1.1 The Training Process of BP Neural Network**

The training process of the BP Neural Network consists of two parts: the forward propagation of the signal and the backpropagation of the error. The signal is passed from the neural network’s input layer, through the hidden layer, to the output layer, where the output signal and error signal are generated. If the error signal meets the requirements, the calculation ends; otherwise, the signal is transferred to backpropagation. The weights and thresholds are adjusted layer by layer, and the network parameters are updated through the gradient descent strategy. The training flow chart of the LM-BP Neural Network is as follows.

1. **Determining the Neural Network Structure.** That is, determine the number of neural network layers and the number of hidden nodes in each hidden layer. Usually, after many attempts, the value of *n* that makes the model prediction effect optimal is obtained.

2. **Initialize weights and thresholds.** Initialize the weights between the input and hidden layers, the threshold, and the learning rate between the hidden and output layers. Each connection weight and the threshold is usually assigned a random value in the interval (-1,1).

3. **Forward propagation calculation.** Through the forward propagation of the determined network, calculate the hidden layer output *Hj*, the output layer output *Ok*:

*Hj* = *f*(∑*n i*=1

*Wij* + *aj* )*, j* = 1*,* 2*, . . . , L* (1)

*Ok* =∑*n i*=1

*WjkHj* + *bk, k* = 1*,* 2*, . . . , m* (2)

Where *Wij* is the weight from the input layer to the hidden layer, *aj*is the hidden layer threshold, *L* is the number of hidden layer nodes, *Wjk* is the weight from the hidden layer to the output layer, *bk* is the output layer threshold.

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Figure 3: Algorithm flow chart of LM-BP

4. **Error calculation.** The prediction error is the difference between the expected value *Yk* and the predicted value.

*ek* = *Yk − Ok, k* = 1*,* 2*, . . . , m* (3)

5. **Weight update.** The weights in the established neural network are updated and adjusted according to the calculated prediction error *ek*. The calculation formula is as follows, *η* is the learning rate constant.

*Wij* = *Wij* + *ηHj* ((1 *− Hj* )*xi*∑*m k*=1

*Wjkek*) *i* = 1*,* 2*, . . . , n*; *j* = 1*,* 2*, . . . , L* (4)

*Wjk* = *Wjk* + *ηHjek j* = 1*,* 2*, . . . , L*; *k* = 1*,* 2*, . . . , m* (5) 6. **Threshold update.** Update the thresholds *aj, bk* according to the prediction error *ek*:

*aj* = *aj* + *ηHj* (∑*m k*=1

*Wjkek*)*, bk* = *bk* + *ηek* (6)

7. **Iteration stop condition.** Iteratively update the parameters until the minimum mean square error is less than the set value, the iteration terminates, and the BP Neural Network training ends.

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**4.1.2 Introduction to the Principle of LM Algorithm**

When BP neural network predicts Bitcoin price, there is a phenomenon of "overfitting," and the gradient descent algorithm will also make it fall into a local optimum. The convergence speed is also slow. In order to improve the price prediction effect of gold and bitcoin, this paper uses the Levenberg-Marquardt algorithm to improve. This section mainly introduces the principle of the LM algorithm.

LM can be thought of as a combination of steepest descent and the Gauss-Newton method. The algorithm behaves like a steepest descent method: slow but guaranteed to converge when the current solution is far from the correct one. When the current solution is close to the correct solution, it becomes a Gauss-Newton method.

Since the establishment of the subsequent LM-BP Neural Network mainly relies on implement ing the LM algorithm in the MATLAB toolbox, we will not introduce too much mathematical knowledge involved in the algorithm. Nevertheless, to help readers understand the algorithm prin ciple of LM more intuitively, combined with the research of K. Madsen et al. (2004) [17], we try to give the pseudo-code of the LM algorithm as follows.

**Algorithm 1:** Levenberg-Marquardt method

**Input:** Historical prices for gold, bitcoin

**Output:** Predicted prices for gold, bitcoin

**1 begin**

**2** *k*:=0; *ν*:=2; x:=*x*0

**3** A:= J(*x*)*T* J(*x*); *g*:= J(*x*)*Tf*(*x*)

**4** *found*:=(*∥g∥∞ ≤ ε*1); *µ*:=*τ*\*max{*aii*}

**5 while** *(****not*** *found)* ***and*** *(k < kmax)* **do**

**6** *k* := *k* + 1; *Solve*(A + *µ*I)**h**1*m* = *−g*

**7 if** *∥****h***1*m∥ ≤ ε*2(*∥x∥* + *ε*2) **then**

**8** *found*:=**true**

**9 else**

**10** *xnew* :=x+*%*

**11** *%* := (*F*(*x*) *− F*(*xnew*))*/*(*L*(0) *− L*(**h**1*m*))

**12 if** *% >* 0(*step acceptable*) **then**

**13** x:=*xnew*

**14** A:= J(*x*)*T* J(*x*); g:= J(*x*)*Tf*(*x*)

**15** *found*:=(*∥g∥∞ ≤ ε*1)

**16** *µ* := *µ ∗ max{*13*,* 1 *−* (2*% −* 1)3*}*; *ν* := 2

**17 else**

**18** *µ* := *µ ∗ ν*; *ν* := 2 *∗ ν*

**19 end**

**20 end**

**21 end**

In the above algorithm ,*f* is an assumed functional relation which maps a parameter vector *p ∈ Rm* to an estimated measurement vector *xnew* = *f*(*p*)*, xnew ∈ Rn*. The basis of the LM

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algorithm is a linear approximation to *f* in the neighborhood of *p*, and find a small*∥δp∥*,where *ε* = *x − xnew*. J is the Jacobian matrix *∂f*(*p*)

*∂p* and contains the first derivative of the network

performance index to the weight and threshold. *µ* is referred to as the *damping term*. And A represents Hessian matrix,*g* means gradient. Among them, the error vector *ν* is composed of the elements of the error matrix arranged in a certain sequence.

**4.1.3 Model Solution and Result Analysis**

When building the model, the Trainlm function in the MATLAB toolbox is used to realize the price prediction of gold and Bitcoin based on the LM-BP neural network. We only need to set the model’s parameters and test the model’s prediction effect—parameter settings.

**Parameter settings.** To satisfy our decision-making needs, we need to make long-term and short-term forecasts for the prices of gold and Bitcoin, respectively. The input data for both are 7-day historical price data, and the short-term forecast output for both is the forecast price for the next day. Taking into account the difference in trading time between the two, the long-term forecast output of gold is the forecast price for the next five days, and Bitcoin is seven days. The figure below shows the topology of Bitcoin’s short-term prediction model.

Figure 4: Bitcoin’s short-term prediction model

In order to avoid overfitting, the sample data is randomly divided for training, and the ratio of training, testing, and validation data is 70:15:15. For gold price prediction, set its hidden layer parameter to 10. For Bitcoin price prediction, set its hidden layer parameter to 16. Use mean square error to measure network performance. When the number of training times reaches 1000, the iteration stops.

**Test of LM-BP Neural Network Prediction Model**. The fitting accuracy of the LM-BP neural network prediction model for gold prices can be generated using Matlab as figure 5.

The figure 5 shows that the *R*2 of the training set, test set, validation set, and the whole is more than 0.99. The same conclusion can be drawn by looking at the fitted accuracy plot for Bitcoin. The predictions of the model we built worked well.

In order to make the readers feel the prediction accuracy of the model more intuitively, we compared the actual and predicted prices of gold and bitcoin and drew the line chart as shown below. It can be seen that the predicted price curve and the actual price curve almost wholly overlap, once again proving the validity and reliability of our prediction model, which lays a foundation for further trading decisions.

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Figure 5: Fit Accuracy Plot for Gold

(a) gold (b) bitcoin

Figure 6: Predicted price and actual price comparison chart

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**4.2 Recurrent Decision Model**

**4.2.1 Model Description**

In the literature review section, we summarize the commonly used portfolio investment decision making, models. Models based on statistical theory pay more attention to the relationship between various factors that affect prices and have good interpretability. A model that relies on artificial intelligence technology is similar to a "black box." We only need to input relevant data to output the corresponding decision. The latter usually works better but can also "overfit." However, the preconditions of this study are different. We can only build the model based on gold and Bitcoin’s historical price data flow. The input is too single, and the degree of adaptation to the above models is not high. Therefore, we consider self-built models rather than improved models.

The idea of building a decision-making model is to determine a specific trading strategy and implement it with an algorithm. Since we can only make decisions based on historical prices, and to avoid situations where the strategy is too complicated to be realized, we use the simplest "buy low and sell high based on trend forecast" strategy to build the model.

On each trading day, we can know the price of gold and bitcoin on that day, so we need to consider the latest data of the day when predicting future price changes, which means that every time we make a decision, we need to update the prediction results and make decisions based on this, so we name the model a Recurrent Decision Model.

**4.2.2 Modeling Process**

Please assume that the investment portfolio of cash, gold, and bitcoin is [C, G, B], and its initial state is [1000, 0, 0] from the meaning of the question. The establishment of the model consists of the following four stages:

⋆ **"Stand by" stage.**

This stage mainly accumulates historical data required for forecasting and does not make decisions. Our decision model relies on forecasting future prices, inputting seven days of historical data into the LM-BP neural network forecasting model for short-term forecasts (both next day’s prices) and long-term forecasts. Since gold and bitcoin have different trading rules, the long-term forecast for gold is five days in the future, while bitcoin is seven days. The decision-making model comes into play when both gold and bitcoin have accumulated seven-day valid historical price data, as shown in the following diagram.

⋆ **Buying stage.**

At this stage, we need to consider two issues: when to buy and how to determine the buy share.

**Buying Conditions (Assume Buying on Day** *t***)** .**Gold** buying conditions: predict that the price increase ratio on the *t* + 1 day is greater than 2% or the increase ratio in the next five days is greater than 3%. **Bitcoin** buying conditions: predict that the price increase ratio on the *t* + 1 day is greater than 3.5% or the increase ratio in the next five days is greater than 4.5%.

**Calculate the Sharpe ratio.**In actual investment, we should try our best to reduce investment risk in the pursuit of maximum return. For this, we introduce the concept of the Sharpe ratio. The

Team # 2218931 Page 14 of 25 Figure 7: "Stand by" stage

Sharpe ratio is used to calculate how much excess return a portfolio generates per unit of total risk exposure. The Sharpe ratio for gold and Bitcoin is calculated as follows.

*Sharpe ratio* =*expected rate of return*

*std of gold or bitcoin over the past seven days* (7)

Among them, the expected rate of return takes the larger of the short-term rate of return or half of the long-term rate of return ( because the risk of long-term holdings is higher). If the Sharpe ratio is greater than 1, it means that the return on our investment is higher than the risk of volatility; if it is less than 1, the opposite is true. We calculate the Sharpe ratio for each portfolio. The higher the value, the better the portfolio.

**Shares are determined based on the Sharpe ratio.** There are two situations we need to consider :

• Buy gold and bitcoin at the same time for the day.Calculating and normalizing the Sharpe ratios for gold and Bitcoin separately will yield two buy ratios. Put all the cash be held into the purchase according to the purchase ratio, and the state of the investment portfolio at this time is[0*,* 0*.*99*p*1 *∗ Ct−*1 + *Gt−*1*,* 0*.*98*p*2 *∗ Ct−*1 + *Bt−*1]. Among them, *p* represents the purchase ratio, and *Gt−*1 represents the amount of gold held yesterday,and *Bt−*1 has a similar meaning. *Ct−*1 represents the amount of gold or bitcoin that can be bought today with cash held yesterday. After the purchase, the asset value of the account is updated based on the actual price of gold and bitcoin on the day.

• Only one investment product meets the purchase requirements. If the Sharpe ratio of the product on that day is greater than 1, all existing cash will be used to purchase the product; if it is less than 1, the product will be purchased according to the corresponding Sharpe ratio share of the cash.

If they buy gold, the state of the portfolio at this time is:[0*,* 0*.*99 *∗ Ct−*1 + *Gt−*1*, Bt−*1] or [*Ct−*1 *∗* (1 *− Sharpe Ratio*)*,* 0*.*99 *∗ Sharpe Ratio ∗ Ct−*1 + *Gt−*1*, Bt−*1].

If they buy bitcoin, the state of the portfolio at this time is:[0*, Gt−*1*,* 0*.*98 *∗ Ct−*1 + *Bt−*1] or [*Ct−*1 *∗* (1 *− Sharpe Ratio*)*, Gt−*1*,* 0*.*98 *∗ Ct−*1 *∗ Sharpe Ratio* + *Bt−*1]. Asset value needs to be updated after purchase.

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⋆ **Holding stage.**

When no cash is held, buying operations are not considered. Only selling operations are considered. Note that even if no buying and selling operations are performed, the asset value must be updated.

⋆ **Selling stage. (Assume sell on** *t′* **day)**

Sell it when we predict a fall in the price of gold or bitcoin on day *t′* +1, and the long-term price forecast is trending down. The changes in its investment portfolio are similar to the buying stage, so we will not go into details here. The asset value needs to be updated after the sell operation.

**4.2.3 Model Solving and Results Analysis**

We designed our own algorithm to solve the self-built Recurrent Decision Model. The pseudocode is as follows:

**Algorithm 2:** Algorithm Principle of Recurrent Decision Model

**Input:** Initial state for cash,gold, bitcoin

**Output:** Predicted prices for cash,gold, bitcoin

**1 for** *day=1* **to** *Ttotal* **do**

**2** Gold’s short-term uptrend based on short-term forecast gold and today gold **3** Gold’s long-term uptrend based on long-term forecast gold and today gold **4 if** *gold’s short-term uptrend ≥ 0.02* ***and*** *gold’s long-term uptrend ≥ 0.03* **then 5** Sharpe Ratio of gold based on **max**(Short-term upside values, long-term upside values/2)/**std**(gold value for the last 5 days

**6 end**

**7** BTC’s short-term uptrend based on short-term forecast BTC and today BTC **8** BTC’s long-term uptrend based on long-term forecast BTC and today BTC **if** *BTC’s short-term uptrend ≥ 0.035****and*** *BTC’s long-term uptrend ≥ 0.045* **then**

**9** Sharpe Ratio of BTC based on **max**(Short-term upside values, long-term upside values/2)/**std**(BTC value for the last 7 days

**10 end**

**11 if** *Income ̸*= *0* ***and*** *(Sharpe Ratio of Gold > 0* ***or*** *Sharpe Ratio of BTC > 0)* **then 12 normalization**(Sharpe Ratio of Gold, Sharpe Ratio of BTC)

**13** Sell gold, BTC at the Sharpe ratio

**14 end**

**15 if** *predicted gold is down* ***or*** *predicted BTC is down* **then**

**16** Buy gold, BTC;

**17 end**

**18 end**

Substitute and solve the predicted price according to the above algorithm, and the following conclusions can be drawn: If starting from September 11, 2016, the portfolio investment is carried out according to our quantitative trading decision-making model, then on September 10, 2021, **the initial investment of $1,000 will be the value is $270836.**

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**5 Prove the Model by Providing Evidence**

This section will present evidence that our model provides the best strategy. ⋆ **Verify that the current model parameters are optimal.**

For a specific model, we get the optimal result only when each parameter takes the optimal value. When establishing the circular decision-making model, we determined the minimum increase in buying investment products based on the given transaction costs and financial asset trading experience. In order to prove that the parameters we set are optimal values, parameter optimization is performed.

Let the short-term growth rate threshold of gold is *α*1, and the long-term growth rate threshold is *β*1; the short-term growth rate threshold of Bitcoin is *α*2, and the long-term growth rate threshold is *β*1.

Combined with the known information of the topic and the actual situation, the value range of *α*1 is [2,2.5,3,3.5], and the value range of *β*1 is [3,3.5,4,4.5,5].*α*2 should be in [3.5,4 ,4.5,5,5.5,6], and *β*2 is in [4.5,5,5.5,6,6.5,7,7.5]. We will optimize the parameters with the ultimate goal of maximum profit.Comparing the investment values corresponding to different parameters, we determined the optimal value of *α*1*, β*1*, α*2 and *β*2 are: 2,3,3.5 and 4.5. This result is consistent with the parameters set by our model. The current model has made the optimal strategy only from the model’s perspective.

⋆ **Compared to other strategies, our strategy achieved the highest returns.**

To validate the effect of this model, we decided to use a control group for illustration. Consider long-term trading, short-term trading strategies, and compare the returns of investment companies. We set up the following five control groups and calculated end-of-period asset values. For simple designs, we omit the calculation process.

• **Control Group 1:** At the beginning of the period, September 12, 2016, invest all cash in gold until the end, when the total assets were $1341.276.

• **Control Group 2:** All cash was invested in Bitcoin at the beginning of the period on September 11, 2016, until the end of the period, when the total assets were $73,097.98.

• **Control Group 3:** Investing half of the cash in Bitcoin on September 11, 2016, and the other half was invested in gold on September 12, 2016, until the end of the period, when the total assets were $37,219.593.

• **Control Group 4:**The average annual profit rate of international investment companies has reached 30%, which is outstanding. We assume that the original assets are also expanding at an average annual rate of 30%. After five years, the assets will reach $3712.93.

• **Control Group 5:** Buy Bitcoin with all their funds and conduct short-term trading activities. To better construct the control group, we propose a simple Bitcoin market index, a variation of the BBI index. MA stands for the daily moving average. We define the bitcoin market index as *BBIbiction* = (*MA*3 + *MA*6 + *MA*12)*/*3,*MA*3 indicates the 3-day average price,

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if the bitcoin price is lower than the index, the market is not sluggish. We precisely define a strategy to buy when the price of bitcoin is above the index for three consecutive days and sell when the price of bitcoin is below the index for three consecutive days. A total of 73 buying operations (72 selling operations) occurred under this strategy in five years, and the assets at the end of the period were $3117.2.

Sort our strategies and the asset values of each control group in reverse order and make the following table.

Table 2: Asset Value Comparison of Different Strategies

Classification Strategy Asset Value ($) Ranking

Quantitative Trading our model 270836.00 1 Long-Term Trading Control Group 2 73097.98 2 Long-Term Trading Control Group 3 37219.59 3 Actual Trading Control Group 4 3712.93 4 Short-term trading Control Group 5 3117.20 5 Long-Term Trading Control Group 1 1341.28 6

The data in the table gives us some insights:

1) Our strategy ranked first among several control groups, and the asset value was much higher than the other strategies, indicating that the best strategy was given.

2) Control group 2 is the control group with the highest assets. The price of Bitcoin has risen rapidly in these five years, so the portfolio assets with Bitcoin assets have grown quite rapidly. However, the growth rate of gold is slightly slower due to its properties, such as value preservation. It can be found that the growth rate of investment portfolios containing only gold assets is not excellent.

3) In addition, control group 5 ranks relatively poorly due to trading on only one index, incomplete information, and significant volatility in the Bitcoin market. At the same time, too many transactions will lead to a significant increase in transaction costs, which will affect the income. At the same time, this strategy only considers the past profit and loss situation. It does not predict the future according to the current situation, resulting in the trading effect of this strategy being lower than the long-term trading effect.

**6 The Effect of Transaction Costs on Model Sensitivity**

In this article, transaction costs are mainly represented as commission costs when conducting buy and sell operations because there is no additional cost to hold assets. The total commission cost is closely related to the number of transactions and the percentage of commission paid per transaction. Just imagine, in the same transaction, the change in the commission payment ratio will affect the transaction cost, which will impact the total assets we hold in the end.To explore how sensitive the implementation strategy of this paper is to transaction costs, we decide to adjust the commission payment ratio and observe changes in total assets.

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⋆ **The effect of transaction costs on assets.**

Fixed strategy, only changing the commission payment ratio of Bitcoin and gold observing the impact of changes in transaction costs on total assets.When fixing the strategy, we need to consider three cases: only changing the commission ratio of gold, only changing the commission ratio of Bitcoin, and changing both simultaneously. We used MATLAB to draw a graph of the change in total assets with transaction costs when the strategy is fixed as follows:

Figure 8: Fixed strategy, the impact of transaction costs on assets

From figure 8, it can be seen that:

• When the gold commission ratio remains the same and the bitcoin commission payment ratio changes, the asset changes are pretty obvious. As the commission ratio increases, total assets decrease accordingly.

• When the Bitcoin commission ratio remains the same and the gold commission payment ratio changes, there is almost no change in assets. For example, when the gold commission payment ratio is adjusted to 26%, the optimal asset obtained by the decision-making model is still $270,836. This shows that in this trading strategy, the main trading object is Bitcoin. Bitcoin is quite sensitive to changes in transaction costs, while gold is insensitive to changes in transaction costs due to too little transaction volume.

• The optimal strategy model under the specified commission ratio, the asset change obtained by only adjusting the commission ratio shows a linear relationship with the commission payment ratio.

• **The model is susceptible to changes in the proportion of Bitcoin commissions but not sensitive to changes in the proportion of gold trading commissions.**

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⋆ **The impact of transaction costs on strategy.**

Considering the role of transaction costs in the model, the optimal strategy corresponding to different commission ratios will also change when transaction costs change.

We further adjusted the model to explore the impact of changes in transaction costs on strategies. Most adjustments are made to the buying criteria for gold and Bitcoin. The goal of the transaction is to maximize the asset, which means that we want the benefits of the transaction to exceed the cost. Therefore, we hope that after buying gold or bitcoin, the income obtained exceeds the commission cost of the transaction.

We improved the asset’s buying criteria to a short-term expected return of more than 1 *−* (1 *− Commission payment ratio*)2. The uncertainty of long-term expected rate of return is greater than that of short-term expected rate of return, so the buying standard of long-term expected rate of return is set as the long-term expected rate of return exceeding 1 *−* (1 *− Commission payment ratio*)2 + 0*.*01. We have plotted the relationship between transaction costs and assets when the strategy changes with transaction costs.

Figure 9: Strategies vary with transaction costs , the impact of transaction costs on assets

From figure 9, it can be seen that:

• Gold remains insensitive to transaction costs.

• When the Bitcoin commission payment ratio is higher than 5%, the effect is not apparent; when it is less than 5%, the strategy is highly sensitive to transaction costs. It is expected that the assets will change drastically. Therefore, at this time, the final asset data under the required commission payment ratio has changed to a certain extent compared with the previous strategy.

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After the above analysis, we can find that **both the trading strategy and the trading results are highly sensitive to the change of the Bitcoin commission payment ratio, and less sensitive to the change of the gold commission payment ratio.**

**7 Evaluation of Strengths and Weaknesses**

**7.1 Strengths**

Our model offers the following strengths:

• We use the LM-BP Neural Network Model. Compared with other models such as the arima model and the gray prediction model, the model has higher prediction accuracy and can better fit the data and carry out prediction work. At the same time, we construct a short-term prediction model and a long-term prediction model for gold and Bitcoin respectively.

• When constructing a decision model, using both our short-term forecast data and long-term forecast data for decision-making work, the model is more reliable than using one type of data alone.

• The optimal strategy should consider the maximization of assets and the risks we face when making decisions. In the decision model, we use the Sharpe ratio to divide the purchase share of gold and Bitcoin, considering the risks at different profit rate levels colossal differences. This approach makes the model more relevant to actual market performance and trading operations.

**7.2 Weaknesses and Further Improvements**

Our model has the following limitations and related improvements:

• The decision model we constructed is a greedy algorithm, and the result achieved may not be a globally optimal solution but a locally optimal solution.

• The weight of assets is too concentrated. In the simulated transaction, the main assets traded are bitcoins, and the number of gold transactions is small. The constructed model reflects trend timing thinking and reflects the market a little slower.

• Due to time constraints, the core strategy of the Recurrent Decision Model we established is relatively simple. Considering the complexity of the financial market, we can try to establish a decision-making model based on reinforcement learning strategies in the future.

**8 Memorandum to the Trader**

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MEMORANDUM

**To:** The Trader

**From:** MCM Team #2218931

**Subject:** Quantitative Trading Decision Model and Investment Strategy

**Date:** February 21, 2022

Dear trader,

We are honored to inform you that we have built a quantitative trading decision model based only on historical price data and tried to give the best trading strategy. Our model, investment strategy and results are described below.

***The Model***

At your request, we have developed Quantitative Trading Decision Models that help you determine whether you should buy, hold or sell assets in your portfolio daily.

⮚ Construction idea

∙ Take historical price data as input.

∙ Build a prediction model to predict investment products' short-term and long-termprice conditions.

∙ Determine the investment decision of the day according to a certain strategy.

⮚ LM-BP Neural Network Model

Reliable forecast results are the basis for good investment decisions. It is necessary to build a model with a good prediction effect. The prices of gold and bitcoin are dynamic and volatile and are suitable for prediction by neural network methods. The classic BP neural network uses the gradient descent method to find the optimal value, which often affects the quality of the solution due to the slow convergence speed. Therefore, we established a numerical optimization-based LM-BP Neural Network Model. We tested the model with historical price data, and its 2 *R*exceeded 0.99, and the predictions worked well.

⮚ Recurrent Decision Model

The core idea of the decision model is to make decisions based on the future price trend of investment products. If there is an uptrend in the short or long term and the threshold is reached, buy it, otherwise sell it. We set a threshold related to transaction costs that determine whether to buy or not. We use the Sharpe ratio to measure the riskiness of a portfolio and use it to determine the purchase share of each product in the portfolio.

***Quantitative Trading Decision Model***

*Historical*

*Long and short*

*Price Data*

*term forecast*

LM-BP Neural

Recurrent

Network Model

***Best***

Decision Model

***input***

***Output***

***Strategy***

Schematic diagram of quantitative trading decision model

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***Our Strategy***

Our strategy is to judge the market prospects of future investment products with high forecast accuracy and then use the "buy low and sell high" strategy to make decisions. This is a simple andeffective way to make decisions, primarily when only historical price data is known.

***The Results***

After model solving, model checking, and sensitivity analysis, we can draw the followingconclusions:

✔ We input historical price data into quantitative investment decision-making models for simulated trading. The initial capital is $1,000, and after a five-year trading period, the asset value is $270,836.

✔ The parameters of the model we have established have been optimized. The investment returns are also higher than simple long-term trading, short-term trading, and some high-performance investment companies.

✔ We find that both the trading strategy and the trading results are highly sensitive to the change of the Bitcoin commission payment ratio, and less sensitive to the change of the goldcommission payment ratio.

The above is the summary of our study. We sincerely hope that it will provide you with useful information.

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Team # 2218931 Page 25 of 25 **Appendices**

The figure shows that the *R*2 of the training set, test set, validation set, and the whole is more than 0.99.

Figure 10: Fitting Accuracy Plot for Bitcoin

**Problem Chosen** C

**2022**

**MCM/ICM**

**Summary Sheet**

**Team Control Number** 2224507

**Trading strategies based on voting systems**

**Summary**

In order to better maximize investment returns, traders are always looking to study histor ical price movements in order to develop effective trading strategies. In this paper, we introduce classical factors of stock investment based on the historical prices of bitcoin and gold, and use a mathematical optimization model to calculate the optimal parameters of the factors, and sub sequently form a portfolio investment strategy by composing the factors into a voting system on this basis. An improved investment strategy based on forecasting and risk control is then proposed. Finally, the optimality of the scenarios is analyzed and the extent to which transac tion costs affect the assets and strategies is investigated.

We screened MACD, KDJ and other closing price based stock buying and selling decision factors. Firstly, aiming at the maximum return on investment, a **mathematical programming model** for solving the optimal parameters of a decision factor is constructed by using the data of the first year, and these optimal parameters are calculated by MATLAB. On this basis, the relationship between investment efficiency and these parameters is studied under a single in

vestment strategy composed of one decision-making factor. The results found that: in bitcoin, MACD and WR factors have significantly better returns than KDJ and BOLL indicators under the optimal parameters of a single investment strategy; in gold, MACD and WR factors have significantly better returns than KDJ and BOLL indicators under the optimal investment. Therefore, we selected six factors with better performance, such as DMA, RSI and MACD, to constitute the voting mechanism for investment decision to determine whether to trigger trans

actions. And used the **Mean-Variance model** to determine the proportion of positions when holding two investment products at the same time, thus constituting a portfolio investment strategy. Through the strategy we found that the initial investment capital of $1,000 for 5 years ended up with $125,716.87 in assets and an average annualized return of 162.53%.

Subsequently, to improve the accuracy of triggered trades, we use **LSTM model** to predict the price, and use predictive values in the calculation of investment factors. We also incorporate the **risk control scheme** of forced stop loss into the improved investment strategy. By improv ing we found that the initial investment capital of $1,000 for 5 years ended up with assets of $190,635.58 with an average annualized return of 185.49% which is 14% higher than before.

We also analyze the optimality of the scheme and find that effective factors can improve the return on investment by analyzing the scientific nature of the factors, the calculation of optimal parameters, and the high return on investment perspectives. In addition to this using a mathematical planning model assuming **God's perspective** to arrive at its optimal solution and asset return, we find that the maximum asset in God's perspective is $14,362,722,337.67 and the maximum return generated by our constructed model is only 0.0013% of it. But it is still far better than internationally renowned investment companies.

To better understand the impact of transaction costs on a single factor or investment strat egy, we investigate the change in returns and number of trades for a single factor and invest ment strategy, respectively, when transaction costs change. It is found that an increase in each transaction costs in a single factor leads to a decrease in assets, some factors have a large de crease in the number of transactions with an increase in each transaction costs, and some factors have a slow and stable decrease in the number of transactions. Under the portfolio investment strategy we find that an increase in each transaction costs leads to a decrease in assets, and although the number of transactions decreases, it is more stable overall. This indicates that our strategy is more stable overall and has a better advantage compared to a single indicator.

**Keywords:** Mathematical optimization model; LSTM model; Voting System

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**1 Introduction**

**1.1 Background and Problem Statement**

For market traders the issue of quantitative strategies. On the one hand, traders are con stantly trading at high frequencies to buy and sell assets in order to increase investment returns and reduce losses, which leads to high volatility[1]. On the other hand, traders need to pay a commission for buying and selling, and the prices of the two assets, gold and bitcoin, are also volatile.

Considering the background information and constraints identified in the problem state ment, we need to address the following questions.

⚫ By designing a model and designing the perfect trading strategy based on the price data of the cut-off date, and using the designed strategy and model to calculate the value at the initial value of $1000 on September 10, five years later.

⚫ Provide relevant evidence that demonstrates the best strategy.

⚫ Calculate the sensitivity of strategy to transaction costs and analyze the degree of impact of transaction costs on strategy and final costs.

**1.2 Problem Analysis**

⚫ **Task 1: requires designing a model and optimal strategy and calculating the value after five years.**

In this paper, the closing price based decision factor for buying and selling stocks is screened. In order to be more beneficial for investment, the data optimization model is used to optimize the indicator parameters and the optimal parameters are obtained by MATLAB, after which the voting system is composed and the model is improved. The LSTM model is then used to calculate the investment factor using predicted values and incorporating a risk control scheme of mandatory stop loss.

⚫ **Task 2: requires analysis of the optimality of the strategy.**

This paper first analyzes the scientific validity of the selected metrics and then compares them with the God's perspective investment returns and the investment returns of quality investment companies to demonstrate the optimality of the strategy.

⚫ **Task 3: requires the calculation of the sensitivity and impact of transaction costs.** This paper observes the change in investment returns and the change in the number of trades through the change in transaction costs, and analyzes the impact of transaction costs on the strategy.

**1.3 Our work**

****Figure 1 : Our Work

**2 Assumptions and Justifications**

⚫ **Assumption 1: Bitcoin has no minimum trading unit limit**

**Justification:** The minimum trading unit for Bitcoin is 0.01 BTC, but this is a small per centage of the funds, so this article assumes that there is no minimum trading unit for Bitcoin.

⚫ **Assumption 2: Gold futures without minimum trading unit restrictions Justification:** In order to be able to use all of your money when buying or selling, we ignore the minimum trading unit limit for gold futures.

⚫ **Assumption 3: Not considering systemic risk**

**Justification:** Bitcoin and gold futures trading are subject to full market crashes, such as the bursting of the Bitcoin market bubble, and we have constructed our investment strategy to not consider the possibility of such extreme scenarios occurring.

**3 Notations**

The key mathematical notations used in this paper are listed in Table 1.

Table 1 :Notations used in this paper

**Symbol Description Unit**

*wt*Closing price on day *t*USD

*M*Total Assets USD

*btc B*Number of Bitcoins BTC

*gd B*Amount of gold Per troy ounce

*C*Total Cash USD

*I*Buy Threshold /

*O*Sell Threshold /

**4 Investment Models for Bitcoin and Gold**

In stock and futures trading, investors can measure and judge stock price trends based on external factors such as emergencies and related policies, but this is only a rough analysis of the subjective level, and some technical indicators can usually be used to quantitatively analyze price changes. Currently, domestic and international research has applied these metrics to ma

chine learning models for forecasting in stocks and futu res. In the gold and cryptocurrency space, the trading data properties of gold and cryptocurrencies likewise have very similar char acteristics to those of stocks[2]. Therefore we need to choose some representative and applicable technical indicators for gold and bitcoin in the topic to build a model to determine the timing of buying and selling in the trade.

**4.1 Data preprocessing**

The two data sets given in the question are the bitcoin trading price and gold trading price from September 11, 2016 to September 10, 2021, for a total of 1826 days. Since there is a market closure in gold trading, there is a lack of trading price of gold. For this, we use the previous day's trading price of the missing value as the current day's price for filling. Since the trigger mechanism of each decision factor we selected is mostly price fluctuation, the filling of missing values will not affect the decision factor determination.

**4.2 Bitcoin and Gold Investment Decision Factor Selection**

It has been found that in the securities market, there is a certain correlation between certain indicators and the return of the securities in a specific time period, and such value markers can help us to better select stocks or decide the timing of entry and exit, we call them factors. Factors in the stock market are usually divided into two categories: technical factors and finan cial factors. The technical factors include volume and price indicators, trend, overbought and oversold, energy indicators, pressure support and other types[2].

According to the two datasets given in the question, we can use data such as the prices of bitcoin and gold on different trading days (corresponding to the closing prices in the stock market). We therefore selected factors from the Wind Financial database and the factor library of the Mind Go platform that were calculated using only closing prices and their reconstructed data, and screened for factors that appear frequently in the literature related to quantitative trading strategies. We have selected 7 of these classic factors to use as the basis for building

bitcoin and gold investment models. The KDJ, RSI and WR are overbought and oversold tech nical factors, the MACD, TRIX and DMA are trending technical factors, and the BOLL is a pressure-support technical factor. By consulting the literature, we briefly describe the signifi

cance, calculation methods, and determination signals of some of the factors as follows. **DMA**, or Different of Moving Averager, uses two averages of different periods to deter mine the magnitude of current buying and selling energy and future price trends, with the fol lowing calculation formula defined[2].

*n n*

1 2 1 1

− −

= − ∑ ∑(1)

*DMA n n t w w*

( , , )

1 2

*t i t i*

− −

*i i*

= =

0 0

1

*AMA n n t DMA n n t* =(2)

( , , ) ( , , )

1 2 1 2

10

In equation(1)(2),*wt i* −is the closing price of the day.1 *n*and*n*2are the specific number of days of the long and short periods, which are parameters to be determined. When*DMA*is greater than*AMA*, it is a buy signal; conversely, when*DMA*is less than*AMA*, it is a sell signal.

**RSI**, or Relative Strength Index, RSI compares the average price change on up days with the average price change on down days in an attempt to determine how overbought or oversold an asset is, reflecting the boom in the market over a certain period of time, and is calculated using the formula defined below[2].

100 =100 ˆ

*RSIr*

−

1ˆ*nn*

(3)

+

*f*

In equation(3),ˆ*nr*is the average of the number of up days in the cycle,ˆ*n*

*f*is the average

of the number of down days in the cycle, and *n*is the specific number of days in the cycle. When RSI is greater than*O* , it is considered as a sell signal; when RSI is less than*I* , it is considered as a buy signal.*n* ,*O*and*I*are all parameters to be determined.

**MACD**, or Moving Average Convergence Divergence, is calculated from the difference between two Exponential Moving Average (EMA, also known as Weighted Moving Average) with different speeds (one with a fast rate of change and the other with a slow rate of change). The index is calculated by timing the purchase and sale of stocks and tracking the trend of stock price movement between the Differential value (DIF) and the Difference Exponential Average (DEA) values to obtain the MACD value[2]. The calculation formula is defined as follows.

2 2 ( , ) (1 ) ( , )

*EMA n w C EMA n w*

= + −

*n n*

+ +

1 1

1 1 1

*t t t* −

1 1

2 2 ( , ) (1 ) ( , ) *EMA n w C EMA n w* = + −

*n n*

+ +

1 1

2 2 1

*t t t* −

2 2

*DIF n n w EMA n w EMA n w* ( , , ) ( , ) ( , )

= −

1 2 1 2

*t t t*

(4)

2 8 ( , , ) ( , , ) ( , , ) *DEA n n w DIF n n w DIF n n w* = +

10 10

1 2 1 2 1 2 1

*t t t*

−

In equation(4),1

( , ) *EMA n wt*is the1 *n* -day index-weighted moving average,2 ( , ) *EMA n wt*is the