DREAM: Moving Average Crossover Strategy + Dynamic Programming Model = Wealth Dreams Come True

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Abstract
If investors want to profit in the market, they need to have a reasonable trading strategy. In this paper, we use the moving average crossover strategy to process data, predict the short-term market price situation based on the historical price before the trading day, and also use EMA, RSI and MACD for analysis, in order to ensure that at every stage our portfolio brings maximum profits. We further introduce the upper bound of transaction amount as a constraint, and transform the model from nonlinear to linear dynamic programming model. At the same time, we prove by contradictory method that the optimal solution obtained by the improved model remains unchanged, which shows that the trading strategy obtained by our model is optimal. Due to the nature of dynamic programming, it is provable that our trading strategy is optimal. Taking into account the risks in financial markets, we added a risk control system to the model to help us stop losses in time and reduce profit draw downs. Finally, we changed the number of transactions according to the different commission fees, and then conducted a sensitivity analysis on the commission. The results showed that the smaller the commission, the greater the profit, and the more the number of transactions.

Keywords: *Moving Average Crossover Strategy; Multi-stage dynamic programming model; Trading strategy, Maximum income, Sensitive analysis.*

1.INTRODUCTION

1.1. Statement of the problem

With the growth of national disposable income, people are eager to seek reliable investment methods for the purpose of realizing wealth appreciation. Since the creation of modern portfolio theory in the 1950s by Markowitz [4], as the issuance of various bonds, stocks and other risky assets continues to increase, and the role of risky asset investment in economic development continues to strengthen, countries around the world pay more and more attention to the asset portfolio theory [6].

Among them, trading gold and Bitcoin are the two most popular forms. People trade with the aim of maximizing returns, but what combination of strategies should be adopted is the difficulty faced by traders. Therefore, based on the transaction data of gold and bitcoin, we will select a specific period of time, on the basis of predicted results to design a strategy that maximizes returns during this period. After that, we will examine the impact of trading price changes on the strategy, and finally come to a reasonable conclusion.

1.2. Literature Review

In recent years, programmatic trading has developed rapidly in the financial market, accounting for more than 70% of programmatic trading in the US futures market. Its most obvious advantages are: it can carry out uninterrupted continuous trading, and to the greatest extent overcome the influence of investors' subjective emotions on investment strategies [1]

The traditional securities analysis methods are mainly fundamental analysis and technical analysis. At present, the mainstream technical analysis ideas include the K-line theory, the golden section line theory, and the Dow theory. Although this series of methods is simple, it is difficult to capture the complex nonlinear relationship between various indicators of stock operation, and the effect is often unsatisfactory [2]. Existing forecasting methods utilize linear (AR, MA, ARIMA) and non-linear

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algorithms (ARCH, GARCH, neural networks), but they focus on forecasting stock index movements or price forecasts for individual companies using daily closing prices. M.Karazmodeh, S.Nasiri et al. have tried to optimize the algorithm based on SVM using the improved particle swarm of genetic algorithm (IPSO)[3].

With the advent of new computer technologies, machine learning algorithms are increasingly being used in trading strategies. The advantage of machine learning algorithms is that they can efficiently operate on high-dimensional features. In 2018, Phang Wai San, Tan Li Im and others designed an ensemble neural network using three types of neural networks: Feedforward Neural Network (FFNN), Ehrman Regression Neural Network (ERNN), and Jordan Recurrent Neural Network (JRN), and achieved the forecast results are better than traditional technical analysis methods and time series modeling methods [5]. Some scholars have also applied the LSTM neural network algorithm to the research on the high-frequency data of commodity futures, expecting to build a three-classifier that can accurately predict the short-term trend of high-frequency data of commodity futures based on the LSTM algorithm [7].

1.3. Assumptions

In this section, we will make the following global assumptions; the assumptions specific to each model will be stated and proven in its corresponding section.

- Our trading strategy is based on trend thinking. When there is a continuous unilateral market, we can obtain relatively sufficient profits.
- Our trading indicators have filtered out some of the noise caused by price fluctuations. When a unilateral trend is running, stop-loss selling is not performed due to short-term corrections in price movements.
- Investors only invest a certain amount of free funds at the beginning of the investment, and will not increase their investment in the asset market in the subsequent stages; they will not withdraw the income funds that have been obtained from the asset market. The investor's final holdings of assets are only obtained by n times of buying and selling with the initial free funds.
- In asset investment, short selling is not allowed, and the amount of assets sold by investors is not allowed to exceed their actual asset holdings at that time.
- We determine that the total investment risk is measured by the riskiest of the various assets invested in each stage. Because taking into account the more diversified the investment, the smaller the investment risk. Moreover, investors' investment risk requirements cannot be higher than a fixed risk ceiling.
- The investment is continuous, and there is no other behavior between adjacent two stages. In this way, the investor's assets at the end of any phase are the same as at the beginning of the next phase.
- It is assumed that no inflation occurs during this period, and the time value of money is not considered. The imminent effect of time on the currency is negligible.
- The minimum trading volume for gold is 0.01 ounces, and the minimum trading volume for Bitcoin is 0.00001btc.

1.4. Abbreviations and Symbols

Table 1: Abbreviations and Symbols.

SYMBOLS	DEFINITION
i	Indicates the type of investment product: Gold(g) or Bitcoin(b)
j	represents the j investment phase
α_i	Commission cost
bos_i^j	In the j stage, the buy and sell signals of gold/bitcoin given by the trading system. ($bos_i^j = -1 : buy$; $bos_i^j = 1 : sell$; $bos_i^j = 0 : position$)
s_i^j	The value of Gold/Bitcoin owned by investors at the beginning of phase j
t^j	Amount of free funds from investors at the beginning of phase j
x_i^j	Transaction Amounts for the Gold/Bitcoin respectively at the beginning of the j phase ($x_i^j > 0 : buy$; $x_i^j < 0 : sell$; $x_i^j = 0 : position$)
Q	The upper limit of risk that investors can bear
q_i^j	Average risk loss ratio

(s_g^j, s_b^j, t^j)	At the beginning of the j phase, the status of the amount of holding assets and the amount of free funds
(x_g^j, x_b^j)	Investment decision variables at the beginning of the j phase

2.MANUSCRIPT PREPARATION

Our main goal is to solve three problems that need to be explored: the first step is to design the optimal strategy for trading and calculate the maximum gain obtained during the trading period; the second step is to prove that the strategy provided by our model is the best; the third step explores the sensitivity of the transaction price and its impact on the results.

In order to solve these problems, we first analyze the data, use the moving average crossing strategy combined with the dynamic programming model method to simulate the results, and combine the theoretical proof that the obtained figures are the maximum returns, and finally give the transaction cost some disturbance items to observe what impact different transaction costs have on the strategy and results.

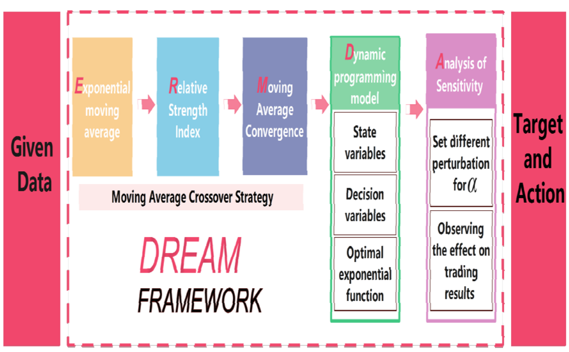

Figure 1: Workflow.

2.1. he dynamic programming model determines the best strategy

2.1.1 Problem Analysis

A trader who wishes to use a certain model to achieve the goal of maximizing profit, the only basis for determining investment behavior is the past daily price flow. When we have an initial capital of $1000, the trading period is from September 11, 2016 to September 10, 2021.On each trading day, the trader decides his portfolio: [C, G, B]. Each transaction incurs a certain transaction cost, assuming αgold = 1% and αbitcoin = 2%, but there are no additional fees for holding the asset. It is worth noting that gold is only traded on market open days, but there is no time limit for Bitcoin to be traded.

Under the premise of satisfying a certain risk tolerance, in order to plan this multi-stage asset investment portfolio problem, we will design a multi-stage dynamic programming decision-making model with the goal of maximizing returns as much as possible. Using the data provided, we propose a moving average crossover strategy to determine how we handle gold and bitcoin assets during the trading day: buy, hold or sell.

2.1.2. Moving Average Crossover Strategy

1) Strategic Analysis

We use a moving average crossover strategy to make trading decisions, one long and one short, to determine their stock price trends. Among them, the short-term moving average can closely follow the trend of the stock, representing the stock price change in the short term;while the long-term moving average has a smaller and more stable response to the stock fluctuation, indicating the long-term stock price change.

Since there is no price data before September 11, 2016, in the first month of trading, the 5-day EMA and the 15-day EMA are used as trading indicators. When the moving averages are aligned in the same direction, the 5-day EMA will cross the 15-day EMA. The daily EMA is used as a buy signal for our trading system; conversely, when EMA5 crosses EMA15 downwards, it is used as a sell signal. From the second month of trading, use the 20-day EMA and the 60-day EMA, the former represents short-term market volatility, the latter represents short-term volatility, plus RSI and MACD indicators for auxiliary judgment.

In addition, we consider all cases where the buy/sell conditions are not met as continuing to hold.

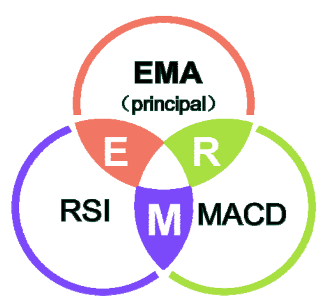

Figure 2: Three indicators for joint decision-making.

a) *Exponential moving average*

Exponential Moving Average EMA is an exponentially decreasing weighted moving average. The weighted influence of each value decreases exponentially with time. The more recent the data has the heavier the weighted influence, but the data with a longer time interval is also given a certain weighted value.

The degree of weighting is determined by α constant value between 0 and 1. It can also be expressed as the number of days N:

$$\alpha = \frac{2}{N+1} \quad (1)$$

Let the actual value of time t be Y_t, while the EMA for time t is S_t ,and the EMA for time t-1 is S_{t-1}. The equation for calculating time t≥2 is：

$$S_t = \alpha \times Y_t + (1-\alpha) \times S_{t-1} \quad (2)$$

Let today's (t) price is p_t， and substitute EMA_{t-1} recursively into ， , then the EMA_t equation for today(t)is：

$$EMA_t = \alpha \times (p_t + (1-\alpha)p_{t-1} + (1-\alpha)^2 p_{t-2} + (1-\alpha)^3 p_{t-3} + \ldots) \quad (3)$$

Theoretically this is an infinite series, and since 1-α <1, the subsequent values will become smaller and smaller, so it can be ignored and only the first *N+1* term is calculated. For the approximately uniform data, the undercalculated part is about $(1-\alpha)^{N+1}$：

$$EMA_{weighted} = \alpha \times \left[1+(1-\alpha)+(1-\alpha)^2+\ldots+(1-\alpha)^N\right] = \left[1-(1-\alpha)^{N+1}\right] \quad (4)$$

When the EMA rises, it can be considered to buy assets, and when it falls, it should be considered to sell, and it can remain unchanged when it goes out, indicating that there is no obvious trend in price movements.

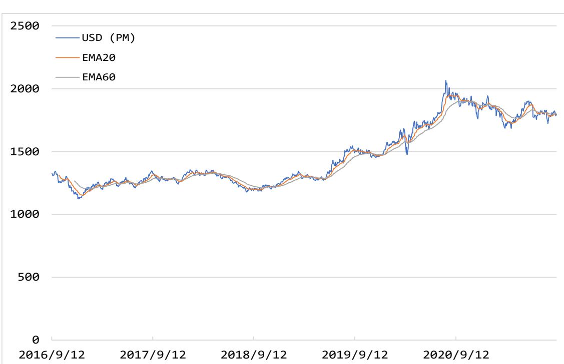

Figure 3: EMA-GOLD.

Figure 4: EMA-BITCOIN.

b) Relative Strength Index

The Relative Strength Index RSI is a technical analysis tool that expresses the strength of prices by comparing price movements. It is a momentum-based oscillator that measures the speed and amplitude of price movements. According to the principle that the rise will fall for a long time and the fall will rise for a long time, the level of the RSI value can be used to determine the timing of trading. When using the RSI as a condition for buying and selling, it is usually necessary to set a regional boundary.

Set the daily upward change to U and the downward change to D. In any case, neither U nor D can be negative.

- On the days when prices rise:

$$U = close_{now} - close_{previous} \quad (5)$$

$$D = 0$$

- On days when prices fall:

$$U = 0$$

$$U = close_{previous} - close_{now} \quad (6)$$

- Same price for both days:

$$U = D = 0$$

The average of both U and D requires an EMA (within n days). The RSI can be derived from the following equation：

$$RSI = \frac{EMA_{(U,n)}}{EMA_{(U,n)} + EMA_{(D,n)}} \times 100\% \quad (7)$$

Among them, the RSI is the Normal Strength Index, the $EMA_{(U,n)}$ is the index average of U in n days, and the $EMA_{(D,n)}$ is the index average of n days.

When a stock's tendency to move in price (up or down) becomes more extreme, the more likely it is that the price movement will reverse. When the RSI reaches

80, the trader should consider selling the asset; When the RSI falls to 30, the trader should buy the asset. However, the large fluctuations in stocks have a certain degree of influence on the RSI, so traders should analyze it together with other indicators.

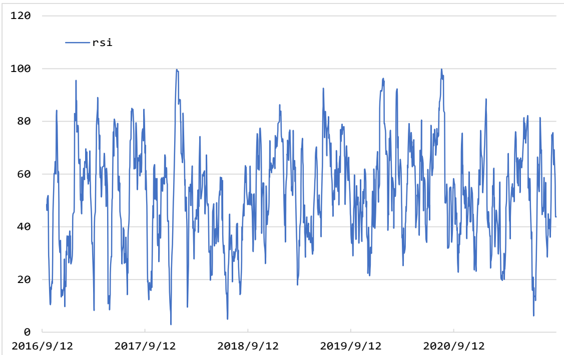

Figure 5: RSI-GOLD.

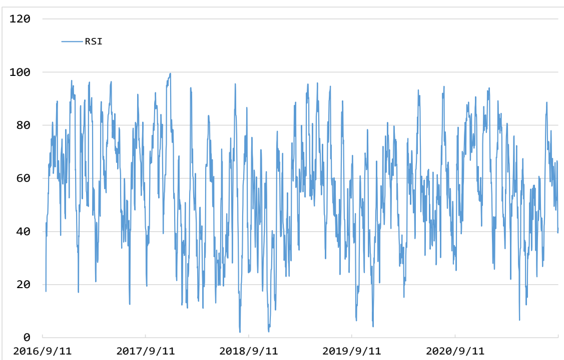

Figure 6: RSI-BITCOIN.

c) Moving Average Convergence

The Exponential Smoothed Moving Average MACD is a common technical analysis tool in stock trading, consisting of a set of curves and graphs calculated from the difference between the stock price or the index's long-term or short-term EMA at the time of closing.

- The deviation value DIF is calculated using the EMA of the closing price (12/26):

$$DIF = EMA_{(close,12)} - EMA_{(close,26)} \tag{8}$$

- The signal line DEM is usually the 9-day EMA of the DIF:

$$DIF = EMA_{(DIF,9)} \tag{9}$$

- A column chart or bar chart can be drawn from the difference between a DIF and a DEM:

$$OSC = DIF - DEM \tag{10}$$

DIF forms a fast line and a DEM forms a slow line. If the stock price continues to rise, the DIF value is positive and getting larger; If the stock price continues to fall, the DIF value is negative and the degree of negative is getting worse and worse. The transaction status can be judged according to the relationship between the DIF value and the DEM value. When the DIF passes through the DEM from the bottom up, a buy signal is issued; Conversely, if it is crossed from top to bottom, a sell signal is issued. When trading signals appear frequently, they need to be analyzed together with other indicators.

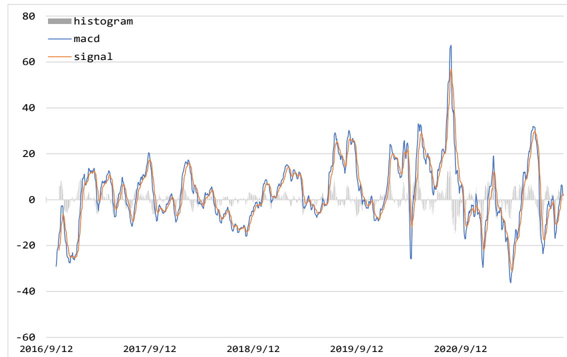

Figure 7: MACD-GOLD.

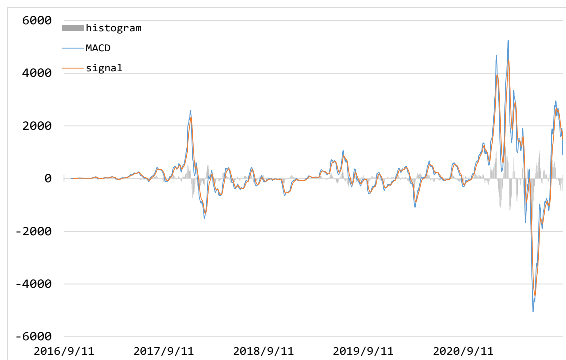

Figure 8: MACD-BITCOIN.

2) Buying Behavior Conditions

- When the moving averages are aligned in the same direction, EMA20 crosses EMA60 upwards.
- RSI > 55.
- Both DIF and DEA of MACD are greater than 0.

Meet the above three conditions, BOS = -1 means buying the asset.

3) Selling Behavior Conditions

- EMA20 crosses EMA60 downwards.
- RSI < 45.
- Both DIF and DEA of MACD are less than 0.

2.1.3. Multi-stage dynamic programming model

1) State variables

We view it as a multi-stage asset portfolio problem. Suppose that consumers make a total of m (m≥1) stages of investment. According to the known conditions, the initial conditions are:

$$s_g^1 = s_b^1 = 0, \quad t^1 = 1000$$

At the beginning of the stage, through the buy and sell signals given by the trading strategy, the asset holdings become:

$$S_g^j + x_g^j, s_b^j + x_b^j \quad (11)$$

(If $x_g^j \neq 0$ is satisfied, then $bos_g^j \neq 0$ is required)

Until the end of the j stage(a new buy and sell signal is obtained at the beginning of the $j+1$ stage), because the price of the holding asset changes, the rate of return at the end of the j period is r_g^j and r_b^j.

Table 2: Numerical meaning of r.

Phenomenon	Meaning
$r_g^j \ / \ r_b^j > 0$	Gold/Bitcoin rate of return has risen
$r_g^j \ / \ r_b^j < 0$	Gold/Bitcoin rate of return has fallen

(Where r_g^j represents the rate of change in the price of gold from the beginning of stage j to the end of stage j, r_b^j stands for Bitcoin's)

Therefore, at the end of the j stage, that is, the beginning of the $j+1$ stage:

$$\begin{cases} s_g^{j+1} = (1 + r_g^j) s_g^j \\ s_b^{j+1} = (1 + r_b^j) s_b^j \end{cases} \quad (12)$$

$$t^{j+1} = t^j - \alpha_b \left| x_b^j \right| - x_b^j - \alpha_g \left| x_g^j \right| - x_g^j \quad (13)$$

So the state transition equation is:

$$\begin{cases} s_g^{j+1} = (1 + r_g^j) s_g^j \\ s_b^{j+1} = (1 + r_b^j) s_b^j \\ t^{j+1} = t^j - x_g^j - x_b^j \\ -\alpha_g \left| x_g^j \right| - \alpha_b \left| x_b^j \right| (t \geq 0) \end{cases} \quad (14)$$

2) Decision variables

According to the fourth assumption (not allowed to sell out), we know that at the beginning of stage, the value of the assets that investors can actually sell cannot exceed their asset holdings at this time.

$$\begin{cases} s_g^j + x_g^j \geq 0 \\ s_b^j + x_b^j \geq 0 \end{cases} \quad (15)$$

In addition, consider that the overall risk of an investor's investment in stage $j(j = 1, \dots, m)$ is generated by the total assets he holds at the end of the stage. Among them, at the end of this stage, the investor's holdings of the $i(i = g, b)$ are $s_i^j + x_i^j (i = g, b)$, so the investment risk of the i asset is $q_i^j (s_i^j + x_i^j)\ (i = g, b)$. Therefore, from the fifth assumption, we know that the overall risk of investors investing in the $j(j = 1, \dots, m)$ stage is:

$$\max_{i=g,b} \{ q_i^j (s_i^j + x_i^j) \} \quad (16)$$

Note that the above formula is non-linear, which can be equivalent to a linear constraint in the following form:

$$q_i^j (s_i^j + x_i^j) \leq Q \quad (i = g, b) \quad (17)$$

To sum up, when the investor's investment state variable at the beginning of the $j(j = 1, \dots, m)$ stage is X_j, the investment decision made by him must satisfy:

$$\begin{cases} q_i^j (s_i^j + x_i^j) \leq Q \\ (i = g, b; j = 1, \dots, m) \\ x_i^j \geq -s_i^j \\ \ (i = g, b; j = 1, \dots, m) \end{cases} \quad (18)$$

After that, we introduce X_k to represent the asset investment transactions of investors in the k stage:

$$\begin{aligned} f_k(X_k, \dots, X_m) &= (t^{m+1} + s_g^{m+1} + s_b^{m+1}) \\ &-(t^k + s_g^k + s_b^k)\ (1 \leq k \leq m) \end{aligned} \quad (19)$$

Indicates that starting from the initial state st_k of the k stage, investors invest in accordance with the decision variable $X_k, \dots, X_m$ in turn, to the actual income obtained when the m stage is over.

3) Optimal exponential function

$$F_k = \max_{X_k \dots X_m} f_k(X_k, \dots, X_m) \quad (1 \leq k \leq m) \quad (20)$$

Indicates that the investor starts from the beginning of the k stage, invests according to the decision variable $X_k, \ldots, X_m$ in turn, and obtains the maximum total return at the end of the m stage. According to the ineffectiveness of decision variables and the relationship between state variables, it can be concluded that:

$$F_k = \max_{x_k}\{F_{k+1}[r_g^k(s_g^k + x_g^k) + r_b^k(s_b^k + x_b^k) - \alpha_g^k\left|x_g^k\right| - \alpha_b^k\left|x_b^k\right|]\} \quad (21)$$

By solving the dynamic programming model, the optimal decision of the investor's investment in m stages can be obtained. Therefore, the investor's investment decision can be represented by a dynamic programming. The basic equation of the dynamic programming is:

$$(\mathrm{I})\begin{cases} F_k = \max_{x_k}\{F_{k+1}[r_g^k(s_g^k + x_g^k) + r_b^k(s_b^k + x_b^k) \\ -\alpha_g^k\left|x_g^k\right| - \alpha_b^k\left|x_b^k\right|]\} \\ s.t.\begin{cases} q_i^j(s_i^j + x_i^j) \le Q \\ (i = g, b; j = 1, \ldots, m) \\ x_i^j \ge -s_i^j (i = g, b; j = 1, \ldots, m) \\ x_g^j + \alpha_g^j\left|x_g^j\right| + x_b^j + \alpha_b^j\left|x_b^j\right| \le t^j \\ (j = 1, \ldots, m) \end{cases} \\ \text{In the above formula:} \\ s_i^{j+1} = (1 + r_i^j)(s_i^j + x_i^j) \\ (i = g, b; j = 1, \ldots, m) \\ t^{j+1} = t^j - \left(x_g^j + \alpha_g^j\left|x_g^j\right| + x_b^j + \alpha_b^j\left|x_b^j\right|\right) \\ s_i^1 = 0, t^1 = M(i = g, b) \end{cases} \quad (22)$$

By solving the dynamic programming model (I), the optimal decision of the investor's m-stage investment can be obtained. Because model (I) is nonlinear, it is more difficult than linear constraints to solve practical problems. Therefore, we consider introducing the concept of an upper bound variable of transaction volume, thereby transforming model (I) into a dynamic programming model with linear constraints and recursive relationships. The specific method is as follows:

Definition 1: If the variable y_i^j satisfies $y_i^j \ge 0$ and $(j = 1, \ldots, m; i = g, b)$, then y_i^j is called the upper bound variable of the transaction amount x_i^j. From definition 1 we know:

$$x_i^j \le y_i^j \text{ and } -x_i^j \le y_i^j \quad (j = 1, \ldots, m; i = g, b) \quad (23)$$

For y_i^j alternative x_i^j, then the model is transformed into:

$$(II)\begin{cases} F_k = \max_{x_k}\{F_{k+1}[r_g^k(s_g^k + x_g^k) \\ +r_b^k(s_b^k + x_b^k) \\ -\alpha_g^k\left|y_g^k\right| - \alpha_b^k\left|y_b^k\right|]\} \\ s.t.\begin{cases} q_i^j(s_i^j + x_i^j) \le Q \\ (i = g, b; j = 1, \ldots, m) \\ x_i^j \ge -s_i^j, -x_i^j \le y_i^j \\ x_i^j \le y_i^j, \ y_i^j \ge 0 \\ \text{all}: (i = g, b; j = 1, \ldots, m) \\ x_g^j + \alpha_g^j\left|y_g^j\right| + x_b^j \\ +\alpha_b^j\left|y_b^j\right| \le t^j \\ (j = 1, \ldots, m) \end{cases} \\ \text{In the above formula:} \\ s_i^{j+1} = (1 + r_i^j)(s_i^j + x_i^j) \\ (i = g, b; j = 1, \ldots, m) \\ t^{j+1} = t^j - \left(\begin{matrix} x_g^j + \alpha_g^j\left|y_g^j\right| + x_b^j \\ +\alpha_b^j\left|y_b^j\right| \end{matrix}\right) \\ s_i^1 = 0, t^1 = M(i = g, b) \end{cases} \quad (24)$$

The relationship between model (I) and model (II) will be discussed in detail in Task 2.

4) Calculations

Trade using the trading strategy given by our dynamic programming model, with an initial amount of \$1,000, an investment period from September 11, 2016 to September 10, 2021, with a final value of \$60,158.37.

Table 3: Simulation data results.

Times of transactions	49
Times of profit	25
Times of losses	24
Net profit($)	59158.37
Maximum drawdown	26.11%
[C,G,B]	[28.71,6.11,1.0408]

It is important to note that the results we can get can only be local optimal, not absolute optimal, because no one can 100% accurately know the overall market conditions and changes in advance.

The daily returns for investment over the specified time period range as follows:

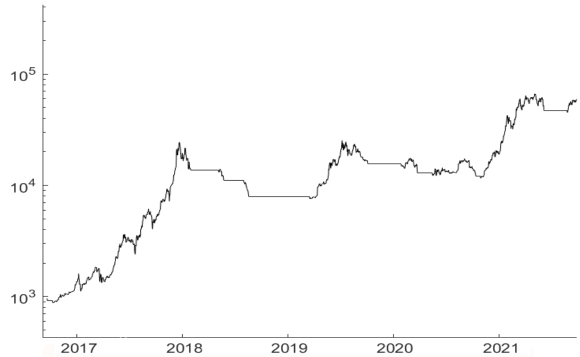

Figure 9: Yield curve.

2.2. Proof of the best trading strategy

Because model (I) is nonlinear, it is more difficult than linear constraints to solve practical problems. Therefore, we consider introducing the concept of an upper bound variable of transaction volume, thereby transforming model (I) into a dynamic programming model with linear constraints and recursive relationships. The specific method is as follows:

Definition 2: Comparing the forms of model (I) and model (II), we can know that if $X = (X_1, \dots, X_m)$ is the optimal solution of model (III), then $XY = (X_1, \dots, X_m, Y_1, \dots, Y_m)$ is the optimal solution of model (IV);where $y_i^j = x_i^j (j = 1, \dots, m; i = g, b)$; and their corresponding optimal values are equal.

Definition 3: If $XY = (X_1, \dots, X_m, Y_1, \dots, Y_m)$ is the optimal solution of model (V), then $X = (X_1, \dots, X_m)$ is the optimal solution of model (VI); and their corresponding optimal values are equal.

Because if $XY = (X_1, \dots, X_m, Y_1, \dots, Y_m)$ is the optimal solution of model (VII), simultaneously exist $1 \le k \le m$ make $y_i^k < \left|x_i^k\right|$ .when:

$$y_i^k = x_i^k, \hat{Y}_k = (y_g^k, y_b^k), \quad XY\hat{} = (X_1, \dots, X_m, Y_1, \dots, Y_k, \dots, Y_m) \tag{25}$$

Then $X\hat{Y}$ is the feasible solution of model (VIII), and the target value corresponding to $X\hat{Y}$ is strictly larger than the target value corresponding to XY , which contradicts that XY is the optimal solution of model (IX).

$$\therefore \forall 1 \le k \le m, y_i^k = \left|x_i^k\right| \tag{26}$$

From the above conclusions and the formal comparison between model (X) and model (XI), it can be seen that $X = (X_1, \dots, X_m)$ is the optimal solution of model (XII), and its corresponding optimal values are equal.

2.3. Sensitivity analysis

For sensitivity analysis, we select the economic benefit index of transaction cost as an uncertain factor, and set different disturbances to transaction cost a to make it take a value within a certain range. Comparing the final results, we can see the impact of transaction costs on trading strategies and results:

Table 4: Sensitivity test results.

α_g \ α_b	0.01	0.015	0.02	0.025	0.03
0.005	60795	54180	96516	42958	38218
0.01	60183	59638	59158	58735	58364
0.015	59844	59234	58713	58268	57888
0.02	58772	58007	57434	57006	56686
0.025	59745	59115	58583	58133	57754

It can be seen that when the transaction cost a gradually increases, the final benefit tends to decrease, and when the transaction cost a gradually decreases, the final benefit tends to increase.

3.CONCLUSION

3.1. Strengths and Weaknesses

3.1.1.Model Strengths

- Through the dynamic programming model, it can help us make the best trading decisions to maximize the final profit.
- Our trading model is improved based on trend strategies to reduce frequent stop-loss operations caused by short-term price fluctuations.

- We pursue interdisciplinary fusion solutions that leverage financial knowledge to support our modeling.
- The model used in this paper is generalizable. Based on different considerations, we can easily modify the model.

3.1.2.Model Limitations

- Although the final result obtained by dynamic programming must be the optimal solution, it is only limited to our trading model, so our structure is essentially a local optimal solution, because the parameter settings of the indicators are not necessarily optimal.
- We use a trading model to trade Bitcoin and Gold at the same time, and it is difficult to obtain a better return on investment for both.
- We did not consider the analysis of specific risk factors, such as political factors and geographical factors, nor did we consider the problem of diminishing marginal returns.

3.1.3. Achievement

With the growth of financial consumption activity, traditional securities analysis methods can no longer satisfy consumers' pursuit of maximizing benefits. In this article, we use a combination of moving average crossover strategies and a multi-stage dynamic programming model to arrive at an optimal trading strategy.

First of all, investors can decide to buy, sell or hold positions on the day by means of the moving average crossover strategy. On the premise that the moving averages are arranged in the same direction, buy when EMA 20 crosses EMA 60 upwards, and sell on the contrary. At the same time, with the help of RSI and MACD indicators for auxiliary judgment.

In the multi-stage dynamic programming model, three state variables, decision variables and optimal exponential function are set, and the optimal exponential function is obtained.

We obtained through simulation that during the investment period from September 11, 2016 to September 10, 2021, if you trade according to the optimal trading strategy we gave, you will eventually get $60,158.37. And the result shows that our maximum profit drawdown is 26.11%.

Afterwards, we conducted a sensitivity analysis on the transaction cost, and concluded that the value of the transaction cost will affect the result, and the transaction cost and investment income will change in the opposite direction. The bigger the profit.

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