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Research on Optimization Strategy of Quantitative Investment Scheme Based on Black-Litterman Model

Jinhui Zhang*, Lanlan Shi, Wei Xu

School of Statistical and Applied Mathematics, Anhui University of Finance and Economics, Bengbu, 233030, Anhui, China
**Corresponding author*

Abstract: *In today's trading market, for every investor, they want to obtain a higher rate of return within their own controllable risks. And how to obtain a maximum yield is undoubtedly a complex and difficult challenge. In order to help investors obtain a higher return in gold and bitcoin investment, we have integrated XGBoost, ESN, Black-Litterman and other models to establish a more optimized quantitative investment plan. Task 1: For the model, first use the optimized XGBoost-ESN model to predict the prices of gold and Bitcoin on the second day, and then use the Black-Litterman model to help investors make more accurate quantitative investments. From the initial $1,000 to the final $20,278.14, the annualized rate of return: 82.56%. Task 2: In order to predict the accuracy of the price, we use two different price prediction methods for prediction. The weights of the two are determined by the least squares method, and the optimized model is obtained. And in order to understand that our investment cycle is the optimal solution, we used different trading cycles of 5 days, 15 days, and 30 days for gold and Bitcoin to conduct a single-variable comparison test, and obtained different optimal transactions between the two cycle. Task 3: We conduct a dynamic analysis of transaction costs, and determine the optimal transaction cost range for gold and Bitcoin by understanding different transaction costs. Task 4: Since different investors have different risk acceptance levels, we have added var risk prediction content. In order to reduce the loss of income, we set a profit and loss line to ensure the safety of funds. Finally, we discuss the problems that may arise in the process of practical application of the model, and use the validity test to verify the validity of the established model. In addition, we provide a reasonable evaluation of the strengths and weaknesses of the model.*

Keywords: *XGBoost, ESN, Black-Litterman, Quantitative Trading, Asset Allocation, VAR*

1. Introduction

1.1 Problem Background

Investment is a profit-making business activity in which monetary income, or any other wealth owner whose value can be measured in monetary terms sacrifices current consumption, purchases or purchases capital goods in order to realize value appreciation in the future. Investment and wealth management is also the scientific management of the financial status of the wealth subject itself, to achieve the purpose of preserving and increasing the value of its own wealth.[1-2] In a fast-moving trading market, where the value of different assets fluctuates continuously, traders maximize their total returns by constantly buying and selling volatile assets[3]. Investors generally choose to choose different assets (such as stocks, bonds,...) in the market and optimize the investment portfolio of the selected assets, to reduce investment risk and obtain higher investment returns[4-5].

1.2 Restatement of the Problem

In order to develop a model based on the data given and use only the daily prices to date to determine whether traders should buy, hold, or sell assets in their portfolio daily, the following 5 questions are mainly addressed:

●Develop model that provides the best daily trading strategy based only on price data up to the day[6].

●Using the developed model and strategy, calculate how much the original $1,000 is now worth on September 10, 2021.

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●Prove that the model provides the best strategy.

●Determine the sensitivity of the strategy to transaction costs.

●Determine how transaction costs affect strategies and outcomes [7].

1.3 Our Work

The purpose of this article is to predict the price trend of gold and Bitcoin the next day based on the data so far and based on the optimized XGBoost-ESN model, and then establish the Black-Litterman model to help investors make more accurate quantitative investments[8-9]. In order to take into account the risks in the investment process, we have also established a VAR-based historical simulation model to evaluate the risk of the day's investment to ensure the highest returns under controllable risks. And we use two different forecasting price methods, use the least squares method to determine the weight of the two, and get the optimized model[10]. The distribution is shown Figure 1.

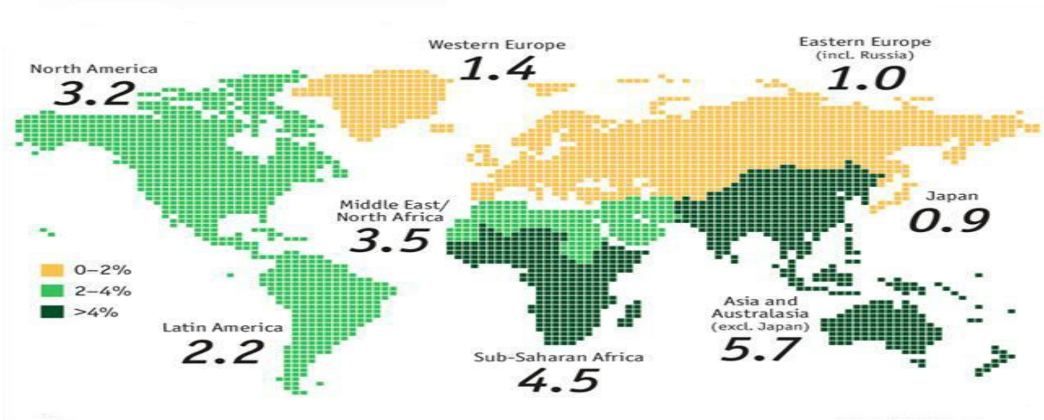

Figure 1: Bitcoin Global Distribution

Furthermore, a single-variable comparison experiment was conducted on the trading cycles of gold and Bitcoin, and the optimal trading cycles of the two were obtained[11]. In addition, we conduct a dynamic analysis of transaction costs and obtain the optimal transaction cost for gold and Bitcoin. Finally, we evaluate the model in terms of scientificity, stability, and applicability.

2. Assumptions and Notation

2.1 Assumptions

a. The data given in question can objectively reflect the reality.

b. Assume that there will be no factors such as war that affect the price of gold during the forecast period.

c. Assuming that during the forecast period, the national policy is stable and the price of gold is independent of political factors.

2.2 Symbol Description

The relevant symbols are as Table 1.

Table 1: Symbols and Notations

Symbols	Definitions
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
FII	Funding Investment
VAR	Value at Risk
R_t P_t	Rate of Return Closing Price on Day t

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3. Model

3.1 Price Prediction of XGBoost Model

The XGBoost model is an improved gradient decision tree algorithm. The core of the algorithm is continuous iteration, and the residual error of the previous tree is fitted by the new tree pair to ensure that the prediction achieves higher accuracy[12-13]. This algorithm can better predict the price of Bitcoin and gold, reduce the prediction difference of the data, and improve the accuracy of the actual prediction. Its main operation process is as follows:

$$\hat{y} = \Phi(x_i) = \sum_{K=1}^{K} f_k(x_i), f_k \in F \tag{1}$$

$\hat{y}$ represents the predicted value of the model. K represents the number of numbers.F is the set of all possible hypotheses.

The objective function of the XGBoost model consists of the following two parts:

$$L = \sum_{i=1}^{n} \iota(y_i, \hat{y}) + \sum_{K=1}^{K} \Omega(f_k) \tag{2}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \tag{3}$$

$\iota(y_i, \hat{y})$ represents the error of the training process.Ω represents the complexity of the model.λ and γ represent the weight of the penalty term.

In order to reduce the loss of the original function during the model iteration process, the following new functions are added to ensure that the iterative process proceeds normally.

$$O_{bj} = L + c \tag{4}$$

$$O_{bj}{}^{(t)} \approx \sum_{j=1}^{T}[(\sum_{i\in I_j} g_i)\omega_j + \frac{1}{2}(\sum_{i\in I_j} h_i + \lambda)\omega_j{}^2] + \gamma T \tag{5}$$

$$= -\frac{1}{2}\sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \lambda T, (G_j = \sum_{i\in I} g_i, H_j = \sum_{i\in I} h_i) \tag{6}$$

T is the number of leaves. ω represents the weight of the leaf. c is a constant term.

The XGBoost model uses the second derivative of the loss to accelerate the convergence of the prediction process function and reduce the complexity of the model. A penalty term is added during model training to prevent overfitting of the prediction function. The final degree of prediction is shown in Figure 2.

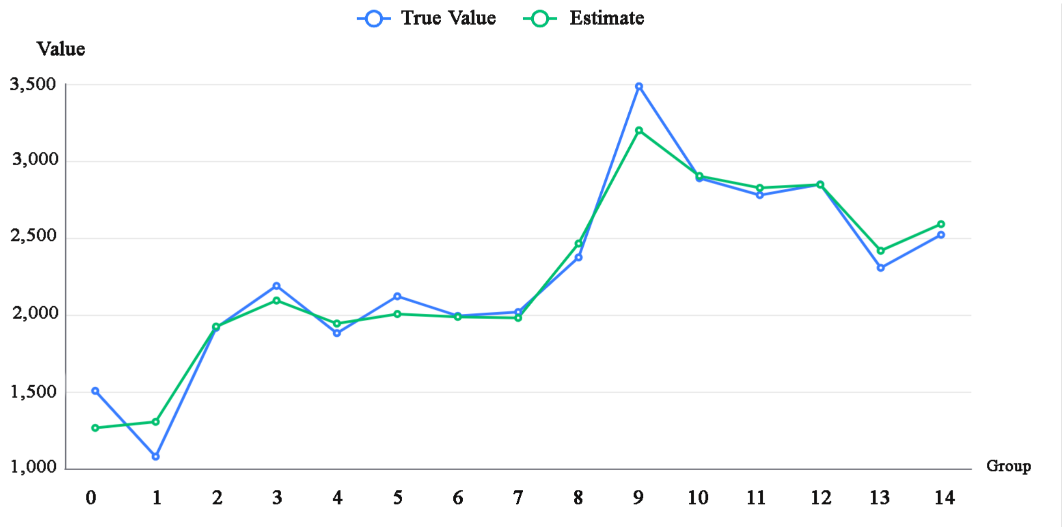

Figure 2: XGBoost Model Prediction Results

3.2 Price Prediction of ESN Model

For the prices of Bitcoin and gold, we use the improved XGBoost-ESN comprehensive optimization model to predict them.

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ESN is a new type of recurrent neural network, which has high application value in time series forecasting[14]. Its core is that the reserve pool contains a dynamic space that changes continuously and randomly, and uses the internal dynamic combination to continuously output the optimized combination.

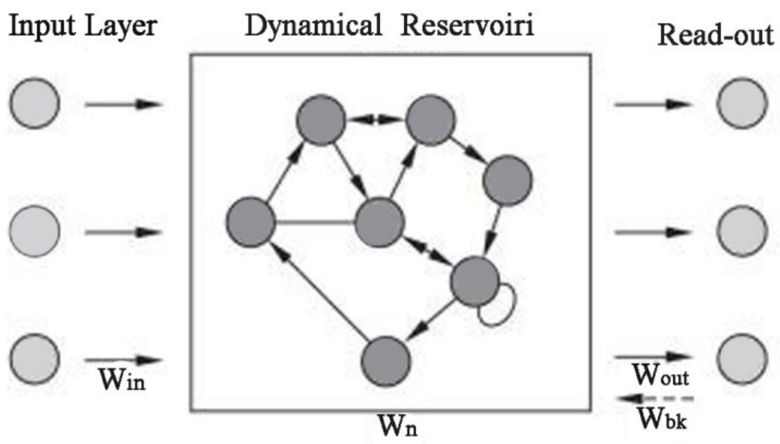

Figure 3: ESN Model Process

As can be seen from the figure 3, ESN includes an input layer, a reserve pool, and an output layer. Compared with the traditional network using weight update, its ESN model operates faster, and the local value does not appear extremely small[15-16].

The data is randomly given during training, and the optimal solution to the output weight is obtained through internal training. The specific process formula is as follows:

$$X(n+1) = f[I_s \cdot W \cdot \mu(n+1) + W_n \cdot X(n) + B_s \cdot W_{bk} \cdot +B_S \cdot W_{bk} \cdot y(n) + \theta] \quad (7)$$

$$y(n) = W_{out}X(n), W_{out} = y(n)X(n)^{-1} \quad (8)$$

The final forecast is shown in Figure 4.

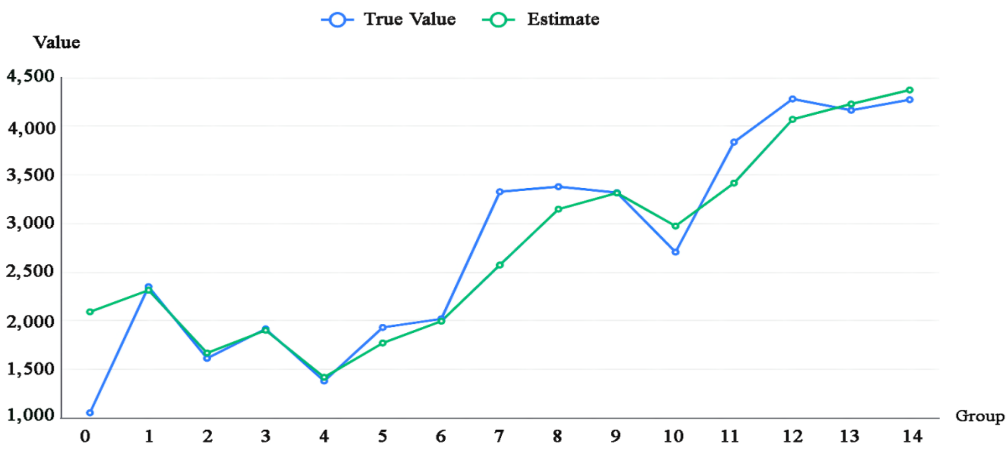

Figure 4: ESN Model Prediction Results

3.3 XGBoost-ESN Optimization Model Prediction

By optimizing the XGBoost model and ESN, we combined the two types of models into one, using the least squares method and taking the corresponding weights, respectively, to obtain the optimized XGBoost-ESN combined model.

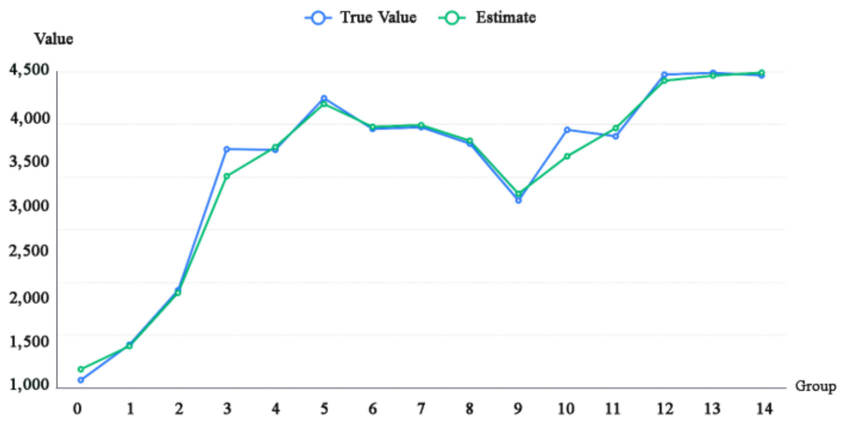

Figure 5: XGBoost-ESN Model Prediction Results

The specific process is shown in the Figure 5. This model will be used to predict the price of gold and bitcoin.

The new method used to predict the future prediction is shown in the Figure 6.

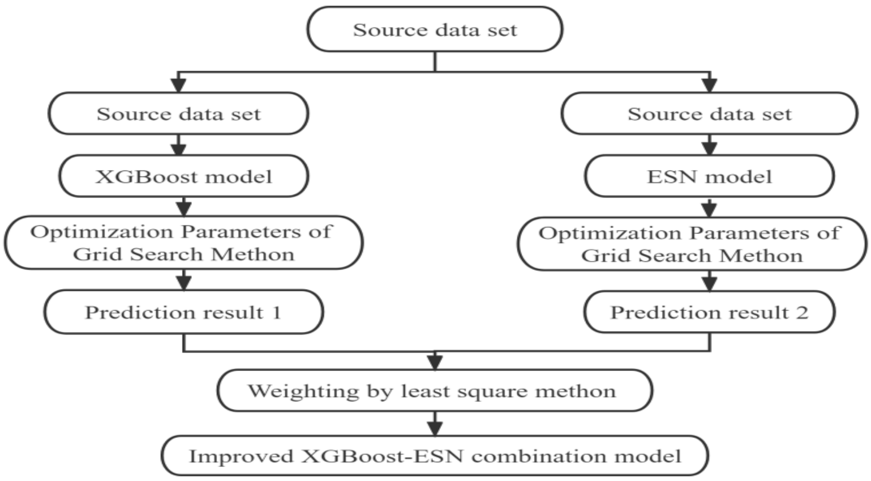

Figure 6: XGBoost-ESN Model

3.4 Quantitative Investing in the Black-Litterman Model

Black-Litterman model, the main research direction of its model, is the practical operation of investors in the actual investment process. It mainly solves the risks encountered by investors in the face of realistic trading and optimizes the real self-substantive problems. Although in real life, the return on investment is impossible for everyone to predict[17]. However, combined with the XGBoost-ESN model's price prediction for gold bitcoin, its Black-Litterman model has greatly improved the asset allocation income. Its utility function formula is as follows:

$$S = \alpha' \Psi - \gamma \alpha' \Sigma \alpha \tag{9}$$

α represents the weight of gold and bitcoin.Ψ represents the excess return vector in the market.Σ represents the covariance vector matrix of excess returns for gold and bitcoin. γ represents the risk aversion index, we use the index in the XGBoost-ESN model.

Investors' opinions will be used as the conditional distribution, and the actual problems in reality will be quantified and assessed to determine an actual model that is more in line with the investors themselves. The conditional distribution model is as follows:

$$PX = R + \varepsilon, \varepsilon \backsim N(0, \Omega) \tag{10}$$

P is a selection matrix. Each row holds N views represents the weight of investors' investment views on gold and Bitcoin itself. R is a return matrix, and its value is obtained according to the

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subjective judgment of the market. Here, it is obtained through the prediction of the previous XGBoost-ESN model. Ω is a covariance matrix. The specific data needs to be determined according to the data selected by investors.

Through XGBoost-ESN's price forecast, we have a clear risk perception of the gains one day after the trading day, and the Black-Litterman model will guide us to the risks and expected returns of buying and selling gold and Bitcoin. For different amounts invested by investors, investors will bear different risks according to different amounts. Here, we assume that the investor will sell half of the asset when the return on the asset exceeds 40%, when the gain exceeds 60%, we will sell all assets, and when the gain or loss is 30%, gold or bitcoin will sell half, when the profit or loss is 40%, the liquidation process will be realized. Finally we get the following benefits: The change process is shown in the Figure 7.

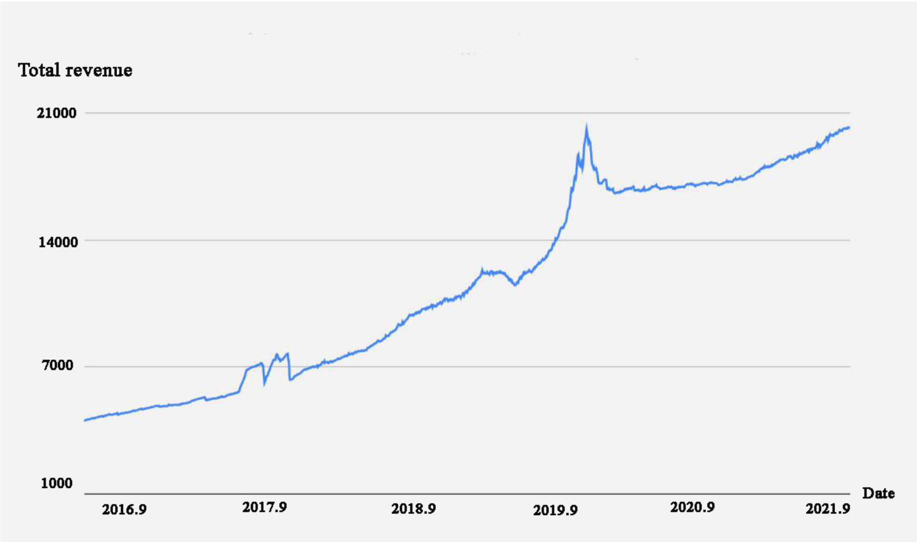

Figure 7: Total Revenue

From the graph we can see that on September 11, 2016, the asset was $1000. Five years later, on September 10, 2021, our assets will be $20,278.14, equivalent to an annualized rate of return of 82.56%.

4. Model Optimal Policy Proof

4.1 Optimization Proof of Model Accuracy

4.1.1 Use the XGBoost and ESN Models to Predict the Case

Using time series forecasting for quantitative trading strategies, we concluded:

That the prices of bitcoin and gold have a very significant impact on the implementation of quantitative trading strategies, and the prices of bitcoin and gold have always been the primary reference for people to trade, so the price analysis becomes an important analysis goal. For price analysis, this paper uses the machine learning XGBoost regression model and ESN echo state network model to predict the price of Bitcoin and gold. Analysis steps:

a) Establish the XGBoost regression model and the ESN echo state network model through the training set data.

b) Compute the feature importance through the established association of both.

c) Apply the established model to training and testing data to obtain model evaluation results.

d) Due to the randomness of the two, the results of each operation are different. If the training model is saved, the subsequent data can be directly uploaded and substituted into the training model for calculation and prediction.

Note: XGBoost cannot get a definite equation like a traditional model, and the model is usually evaluated by testing the prediction accuracy of the data. The assessment results are shown Table 2.

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Table 2: Evaluation Results before Optimization

	MSE	RMSE	MAE	MAPE	R^2
Training Set	10.361	3.219	2.332	0.176	0.999
Test Set	11.127	3.336	2.185	0.123	0.999

MSE: The expected value of the square of the difference between the predicted value and the actual value. The smaller the value, the higher the model accuracy.

RMSE: is the square root of MSE, the smaller the value, the higher the model accuracy.

MAE: The average value of the absolute error, which can reflect the actual situation of the predicted error. The smaller the value, the higher the model accuracy.

MAPE: is the deformation of MAE, which is a percentage value. The smaller the value, the higher the model accuracy.

R2: Comparing the predicted value with the case of using only the mean, the closer the result is to 1, the more accurate the model is.

Through the test results of the XGBoost model, we can see that the results of the model are more accurate. The above table shows the prediction evaluation indicators of the valid validation set, training set, and test set, and the over-quantified indicators are used to measure the prediction effect of XGBoost. Evaluation through the cross-validation set means that the hyperparameters can be continuously adjusted to obtain a reliable and stable model.

4.1.2 Accuracy Analysis of the Synthesis of the Two Models

The grid search method is used to adjust the parameters of the two models to determine the possible set of each parameter, and finally return an optimal value to adjust the model state to the optimal. Use the improved model to predict the price of bitcoin and gold, and use the least squares method to give weights, respectively, give the model prediction results, and observe the fit degree of the results, as shown in the following Table 3:

Table 3: Evaluation Results Optimization

	MSE	RMSE	MAE	MAPE	R^2
Training set	12077.202	109.896	69.681	1.205	0.999
Test set	20166.392	142.008	96.633	0.616	1

4.2 Proof of Transaction Cycle Optimization

In the given data, we classify the interval, using the 5th, 15th, and 30th days to classify the data and conduct univariate experiments. Predict the data situation of 6 days, 16 days, and 31 days, and then compare with the original data to understand the difference between the actual and the predicted model. Got the following result:

Through the pictures, we found that due to the different degree of price volatility of gold and bitcoin, their trading cycles are also different. Gold is less volatile and is suitable for trading in a 15-day cycle; while Bitcoin is more volatile and suitable for trading in a 5-day cycle. In the other two groups of training for gold and bitcoin, due to their high volatility, the variance of the experimental results is too large, and the group prediction situation is clearly not suitable for price prediction. The final forecast price always revolves around the actual price fluctuation on the second day, which means that different group forecasts for gold and bitcoin prices can achieve better data.

5. Transaction Cost Sensitivity

5.1 Sensitivity of Strategies to Transaction Costs

For the sensitivity test of the trading strategy on the transaction cost, the commission for gold is 1%, and the commission for Bitcoin is 2%. We found that when the commission of gold reaches 2.194%, five days are used as the price forecast for gold. The transaction cycle is too frequent and the transaction cost is high. The forecast period for gold will change from 15 days to 30 days. When predicting the price of Bitcoin, it is found that when the commission of Bitcoin reaches 3.283%, the forecast period of Bitcoin will be changed from 5 days to 15 days. When gold and bitcoin reach their

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respective sensitive points, their respective algorithm steps should be changed for price prediction. Sensitivity analysis is shown in the Table 4.

Table 4: Transaction Cost Sensitivity Analysis

Date	USD	GOLD	BTC	Return rates	Returns
2016/12/10	1.01%	0.00%	98.99%	99.88%	1091.06
2016/12/11	1.00%	0.00%	99.00%	101.02%	1102.18
2016/12/12	1.01%	0.00%	98.99%	100.00%	1102.18
2016/12/13	1.00%	0.01%	98.99%	100.13%	1103.57
2016/12/14	1.01%	0.01%	98.99%	99.61%	1099.21
2016/12/15	1.00%	0.02%	98.99%	100.24%	1101.82
2016/12/16	1.00%	0.02%	98.98%	99.89%	1100.6
2016/12/17	0.98%	0.02%	98.99%	101.64%	1118.6
2016/12/18	0.99%	0.02%	98.99%	99.96%	1118.17
2016/12/19	1.00%	0.02%	98.98%	100.03%	1118.55
2016/12/20	1.01%	0.02%	98.98%	100.55%	1124.75
2016/12/21	0.96%	0.02%	99.01%	103.88%	1168.44

5.2 Transaction Costs Affect Trading Strategy and Results

The main purpose of algorithmic trading is to minimize transaction costs and improve investment returns for investors by designing reasonable trading strategies. Even if a portfolio has some advantages, its return may be lower than expected if its transaction costs are too high. Transaction costs can generally be divided into explicit transaction costs and implicit transaction costs. Among them, explicit transaction costs can be directly observed and measured, mainly including taxes such as commissions, and implicit transaction costs mainly include market shocks, opportunity costs, price increases, and risk choices. Relatively speaking, as an important part of the total transaction cost, the hidden cost is not easy to be directly observed and measured. Therefore, it is theoretically proved that the relationship between the cost of permanent market shock and transaction volume is linear, while the relationship between temporary market shock and transaction volume can be linear or nonlinear.

The key point of algorithmic trading is how to design a reasonable trading strategy according to changes in the market environment to determine the optimal submission time, price, and number of orders. A method to measure the market impact cost is presented, and the famous VWAP trading strategy is proposed under the goal of minimizing transaction cost. The transaction cost borne by investors is analyzed, and the corresponding optimal transaction strategy is given. Judging from the existing research on algorithmic trading, the transaction costs considered in most of the research literature are mainly market shock costs, and less consideration is given to the opportunity cost of orders that are not fully executed due to the market environment and the changes in securities prices in different periods the risks posed.

Implicit transaction costs are not easy to observe and measure directly, but they account for a large proportion of total transaction costs. Investors can reduce the hidden transaction costs in the transaction process by designing a reasonable algorithmic trading strategy. Therefore, how to effectively control hidden transaction costs is crucial for investors. A market shock is a change in price caused by the submission of an order to the market.

Generally speaking, a buy order will make the price go up, and a sell order will make the price go down. In theory, the size of the market shock is the difference between the price when the order was executed and the price when the order did not exist in the market, so it cannot be directly observed and measured from the market. If the changes in the prices of gold and bitcoin are simply caused by a temporary lack of liquidity in the market, the prices will return to their original state after a period of time. This is called a temporary market shock.

6. Trading Strategy Suggestions and Risk Analysis

6.1 Trading Strategy Recommendations

6.1.1 Trading Strategy

Because different investors have different, taken profit lines. We need to make different judgments

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according to each investor's actual risk acceptance ability. For example, some investors don't care about a 30% loss, while some investors say it's unacceptable for a 10% loss. In this model, we adopt the following strategy: when the yield exceeds 40% of the principal, we choose to sell half of the holdings. When the yield exceeds 60%, we believe that the market risk is already too great, and we sell all our positions. When the loss reached 20%, we decided to sell half of our holdings. When the loss has reached 40%, we decided to sell all positions to reduce the loss. The three components are shown in the Figure 8

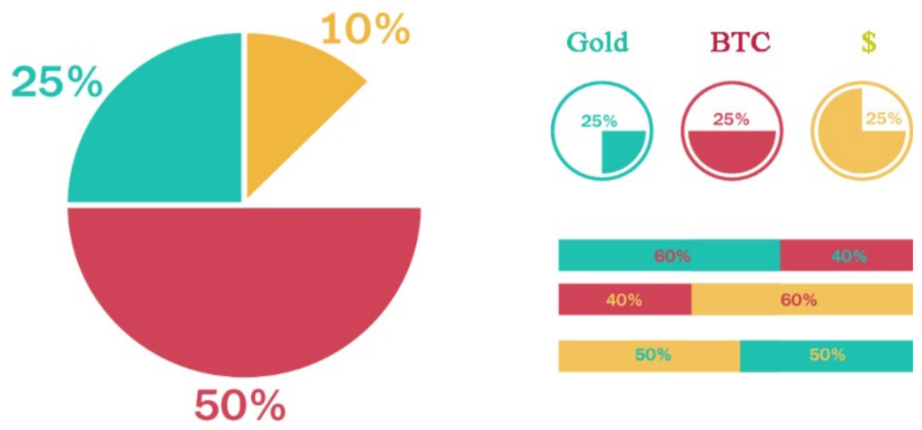

Figure 8: Proportion of Gold, Bitcoin, Dollar

Of course, different investors have different levels of risk acceptance, and the above only represent our recommendations. Due to the complexity of the situation, we have no way to give a specific judgment and can only decide the amount of gold and bitcoin to buy based on the different risk situations that investors accept.

Through the above models, we have obtained good returns on both gold and bitcoin investments, and the annualized return on their transactions is as high as 82.56%. The gain of this profit is mainly attributed to the accuracy of the model establishment and the precise grasp of the taken profit line.

6.1.2 Trading advice

For the buying and selling of gold and bitcoin, we use the optimized XGBoost-ESN model to predict the prices of the two. First, we need to predict the price of the next day through the known data. Then, the trading shares of gold and Bitcoin are judged according to the investor's acceptance of the risk.

For the risk of the second day, we use the VAR risk prediction evaluation to judge whether the investor can accept this rate of return. Finally, we use the Black-Litterman model, which is mainly used for asset allocation, to determine how much each share needs to be bought and sold. The average annual return is shown Figure 9.

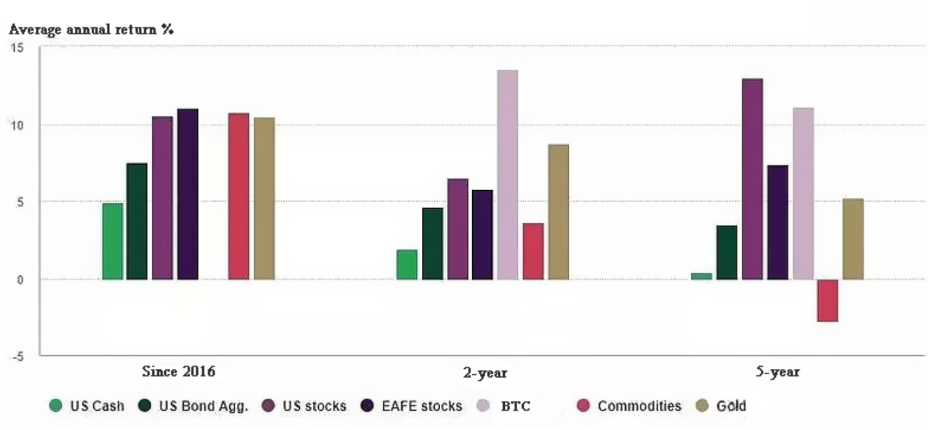

Figure 9: Average Annual Returns of Gold and Bitcoin

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During our model building process, we found that for Bitcoin buying and selling, it is more suitable for short-term operation because Bitcoin is more volatile. Under the condition that the model predicts accurately, it may receive a good gain in the short term. However, due to the existence of transaction costs, operations that are too short in time may lead to high delivery costs and cannot obtain a higher yield. The trading of gold is suitable for a slightly longer-term operation, because the volatility of gold is relatively small, and due to the existence of transaction costs, frequent trading is not suitable. And due to the existence of transaction costs, the commission of gold is 1%, and the commission of Bitcoin is 2%. When the commission of gold reaches 2.194%, the five-day transaction cycle is too frequent, and the transaction cost is high. The forecast period for gold will change from 15 days to 30 days. When predicting the price of Bitcoin, it is found that when the commission of Bitcoin reaches 3.283%, the forecast period of Bitcoin will be changed from 5 days to 15 days.

6.2 Transaction Risk Analysis

Market risk is the main risk in currency trading. This paper introduces the VAR historical simulation method into the measurement of market risk in currency trading, taking gold and Bitcoin as examples, specifically measuring the VAR value of market risk, and judging the size of market risk.

6.2.1 VAR-based Historical Simulation Model

The historical simulation model is a non-parametric method, which makes no special assumptions about the distribution of risk factors, but only a prediction of the present through past situations. The VAR historical simulation model needs to consider three elements: confidence level, holding period, and observation period. Under a given confidence level α, the market risk of margin financing and securities lending based on the VAR historical simulation model can be expressed as:

$$\Pr(r \le r\cdot) = \int_{\infty}^{r} f(r)dr = 1 - \alpha \tag{11}$$

Confidence Level

Confidence level reflects investor preference. Those with a relatively safe investment style tend to choose a higher confidence level, which is generally divided into 90%, 95%, and 99%. The higher the confidence level, the higher the VAR of gold or Bitcoin higher value. However, most studies have shown that an excessively high VAR value may affect the back-testing test, so this paper chooses 95% as the confidence level of the investment. The VAR is shown Figure 10.

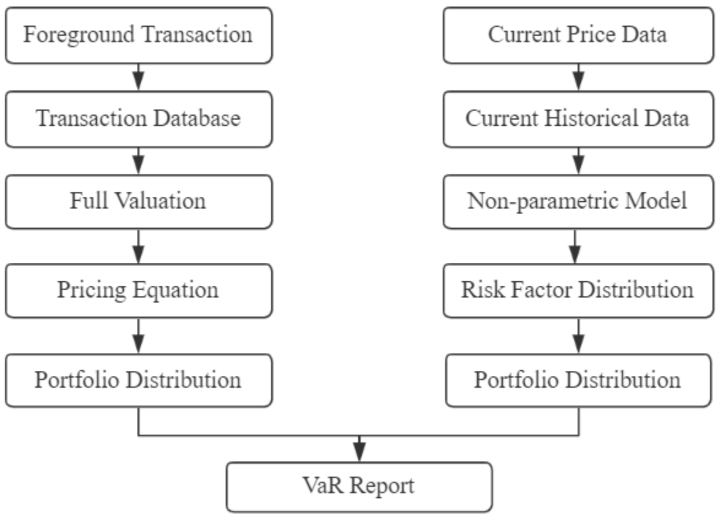

Figure 10: VAR Prediction Process

Holding Period

There are many options for holding periods, such as 1 hour, 1 day, 15 days, or even 1 year. The length of the sample is affected by the length of the holding period. The shorter the holding period, the more samples to choose from. From the perspective of the Basel Committee, a too long holding period is not conducive to early detection of problems, and a too short holding period increases the regulatory

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burden. Therefore, this paper chooses one day as the unit of holding period.

Sample Length

As per the Basel Accord, the sample length is at least one year. This paper selects the sample data of the last two years. In the measurement of currency trading market risk, the process of using the historical simulation method can be simply summarized as follows;

6.2.2 Data Analysis

From the data, we know the closing prices of gold and bitcoin. On this basis, there are generally two methods to calculate the rate of return of gold and bitcoin in different periods arithmetic rate of return and geometric rate of return. This paper selects the geometric rate of return with better statistical properties:

$$R_t = IN(P_t/P_{t-1}) \tag{12}$$

$$R_t \text{ is yield}, P_t \text{ is the closing price on day } t_{\circ} \tag{13}$$

Table 5: Gold and Bitcoin Basic Data

	Minimum	Maximum	Variance	Bias Angle	Kurtosis
Gold	-0.03084	0.025616	-0.000055	-0.264626	1.848278
Bitcoin	-0.176712	0.197759	0.0019241	0.247494	4.129777

From the analysis of the yields of gold and bitcoin which is shown in Table 5, it can be seen from the above table that the variance of the yields of gold and bitcoin is close to 0, and the mean is far from 1, which does not conform to the normal distribution. The kurtosis of gold is close to 2, and the kurtosis of Bitcoin is close to 4, indicating that there is no "spike" phenomenon in the sample data. And the skewness of gold and bitcoin is close to 0, which shows that there is no "thick tail" problem in the sample data. Therefore, the sample data can be analyzed using the historical simulation method.

6.2.3 Empirical Analysis

This paper calculates the currency trading market risk based on the VAR historical simulation model in three steps, that is, the ascending order of return rate, the selection of the corresponding rate of return, and the addition of new data to repeat the first two steps. Taking gold as an example, VAR is calculated as follows:

a)Take January 2, 2018 as an example, set January 2, 2018 as the observation day, and arrange the 324 data before the next day in ascending order.

b) 324* (1-a) =324*0.05=16.2, rounded to 16, select the 12th data in the return ranking as the value of VAR on the observation day.

c) Add the rate of return on January 3, 2018, and repeat a and b to get the daily VAR value, as shown in the Table 6:

Table 6: Gold Risk Table

Time	VAR Value	Time	VAR Value	Time	VAR Value
2018-1-2	-0.066037	2018-1-9	-0.066037	2018-1-18	-0.069641
2018-1-3	-0.066037	2018-1-10	-0.067432	2018-1-19	-0.069641
2018-1-4	-0.066037	2018-1-11	-0.067432	2018-1-20	-0.069641
2018-1-5	-0.066037	2018-1-12	-0.067432	2018-1-21	-0.069641
2018-1-8	-0.066037	2018-1-15	-0.069641	......	......

As shown in the table above, the VAR Value of gold on January 2, 2018 was -0.066037. If the gold position is $1,000, we can guarantee that the maximum loss of gold on that day will not exceed $66.037 at a 95% level.

Similarly, for Bitcoin, it is assumed that January 1, 2018 is the observation day, and the 476 data before the next day are arranged in ascending order, and through calculation, it can be concluded that the 24th data in the return ranking is selected as the VAR of the observation day values, repeat the above steps to get the daily VAR Value of Bitcoin in the Table 7.

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Table 7: Bitcoin Risk Table

Time	VAR Value	Time	VAR Value	Time	VAR Value
2018-1-1	-0.0694096	2018-1-6	-0.0694096	2018-1-11	-0.069845
2018-1-2	-0.0694096	2018-1-7	-0.0694096	2018-1-12	-0.07186589
2018-1-3	-0.0694096	2018-1-8	-0.0694096	2018-1-13	-0.07186589
2018-1-4	-0.0694096	2018-1-9	-0.069845	2018-1-14	-0.07186589
2018-1-5	-0.0694096	2018-1-10	-0.069845	......	......

As can be seen from the above table, on January 1, 2018, the varvalue of Bitcoin was -0.0694096. If the Bitcoin position is $1,000, that is, we can guarantee that the maximum loss of Bitcoin on that day will not exceed $69.096 at the 95% level. ; On January 12, 2018, the varvalue of Bitcoin was -0.07186589. If the Bitcoin position is $1000, that is, we can guarantee that the maximum loss of Bitcoin on the day will not exceed $71.8659 at the 95% level.

7. Model Evaluation

7.1. Advantages

Our model has the following advantages:

a) High scientificity: Use a variety of optimized models to predict the price trend of gold and Bitcoin on the next day, and use a risk assessment model to predict the risk of investment on the day to ensure the highest return within the controllable range of risks.

b) Good stability: We have tested the robustness of the model, and the results show that the model is very robust.

c) Wide applicability: The model we built has no restrictions on the data set and can be applied not only to gold and bitcoin transactions, but also to stocks and funds.

7.2 Disadvantages

Due to the limitation of the given data, the mean value, maximum value, or transaction volume, transaction amount, and other data are not added as parameters for subsequent planning, which may cause certain errors in the prediction results.

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