Problem Chosen	2022 MCM/ICM Summary Sheet	Team Control Number
C		2202981

Trading strategy:

a multi - dimensional market trading decision model

Summary

At present, more and more people choose portfolio investment to buy volatile assets to reduce investment risks and maximize returns. Quantitative investment can overcome human weakness, as well as cognitive bias, so that every decision is justified， and consequently it has been recognized by more and more investors. Through quantitative and computer - programmed buying and selling orders, people can make maximum economic gains.

As for task 1, we divide it into two parts. In task 1(a), data of gold and bitcoin cannot be matched on a daily basis. So, we use Nearest Neighbor Interpolation (NNI) to fill it. And then we employ LSTM (Long Short Term Memory) to predict the value of bitcoin and gold based on the given data, along with Genetic algorithm used to accelerate the convergence of LSTM and optimize the prediction data. In the decision-making process, we construct Quantitative Investment Decision Model (QIDM) to solve the problem. Through this method, investors can master the changes of the investment market, buy and sell assets in time, and optimize the decision.

With regard to task 1(b), based on the predicted data and the real data of the past, we apply QIDM model to determine the optimal trading strategy and maximum return which takes the potential risk loss into account. The introduction of VaR (Value at Risk) is used to measure the risk in the process of trading. Since people tend to invest with less risk in trading, VaR model with larger confidence interval is selected. After that, we use dynamic programming model and objective programming to recurse step by step to get the best daily strategy, which is superimposed to get the maximum return five years later.

As to task 2, based on the model mentioned in task 1(b), we change the transaction commission ratio to change the transaction cost. After obtaining a series of new strategies, we compare the final returns to test the sensitivity of our model to the transaction cost and its impact on the strategy and results.

Last but not least, we summarize the strengths and weaknesses of our model and present our strategies and results to the trader, more or less helping him achieve greater returns in the investment market.

Keywords: Quantitative Investment; LSTM; VaR; Objective Programming; Dynamic Programming

Contents

1 Introduction

1.1 Problem Background

As a barometer of the macro economy, the trading market plays a strong part in national economic development. With the continuous improvement of peoples' living standard and the gradual perfection of the trading market, more and more people get involved in the market trading, expecting the greatest return and the least possible risk.

However, confronted with the complexity and volatility of trading market, it is indeed a struggle for the majority of people, especially for the market traders who buy and sell volatile frequently, to always achieve scientific risk aversion and optimal investment planning. Therefore, investment quantification makes sense all along during the process. Not only does it help people visualize the potential risk, but also it helps market traders make the most use of it and decide the optimal trading strategies.

1.2 Restatement of the Problem

A market trader is about to start with 1000 dollars on 9/11/2016, buying and selling volatile assets, i.e. gold and bitcoin in the problem. Data of the past stream of daily prices up to date are supplied, each having a time label. Our team is asked to determine each day if the trader should buy, hold, or sell their assets in their portfolio based on the in-depth analysis of the data provided, with the to maximize the total return of the initial investment. Moreover, given the existence of commissions, we need to analyze the effect of the transaction costs to the trading strategy.

To achieve our goals, specifically, we will accomplish the following tasks according to the given data:

- Develop a model that decides the optimal daily trading strategy,with the goal to maximize the value of the initial $1000 investment on 9/10/2021.
- Evaluate our model and offer the evidence that it provides the best strategy.
- Find out the effect of transaction costs to the strategy and its sensitivity.
- Write a letter to the market trader by summarizing the analysis, model, and results,and recommending optimal marketing strategy.

1.3 Literature Review

Stock price prediction and trading decision models have always been attached great importance to by researchers. At present, the prediction models are divided into traditional models based on statistical principles and innovative prediction models based on neural networks [1]. At the same time, it is also very important to quantify the risk of stock investment, which attracts researchers to continue in-depth exploration [2].

Previous studies tend to use BP neural network [3] and grey model [4] for stock price prediction, and use VaR and other quantitative indicators for risk assessment [5]. However, research in the field of stock trading decision-making needs to be further studied. In this paper, based on previous studies and improvements, a multi-dimensional trading decision model suitable for gold and bitcoin trading is established, providing a new decision scheme for gold and Bitcoin trading.

1.4 Overview of Our Work

Our main work is focused on two aspects :(1) build a prediction model which matches the existing market data well; (2) Make a objective planning for investment returns and risks to optimize decisions. Then we propose a model called QIDM (Quantitative Investment Decision Model) which help us make trading decisions.

Our model is composed of two main models. One is LSTM (Long Short Term Memory) optimized by Genetic Algorithm. First, we processed and filled the data of gold, and then based on the daily price of gold and bitcoins, we make reasonable forecast, using the forecast data for decision making. The other is QIDM (Quantify Investment Decision Model), which integrates objective programming with dynamic programming. VaR with different confidence intervals are selected to simulate the size of trading risks respectively, so as to obtain the best simulation model. Through QIDM, the benefits can be maximized, and the best strategy for each day can be obtained recursively.

At last, we change the value of commission of bitcoin and gold to verify the sensitivity of our policy to transaction costs.

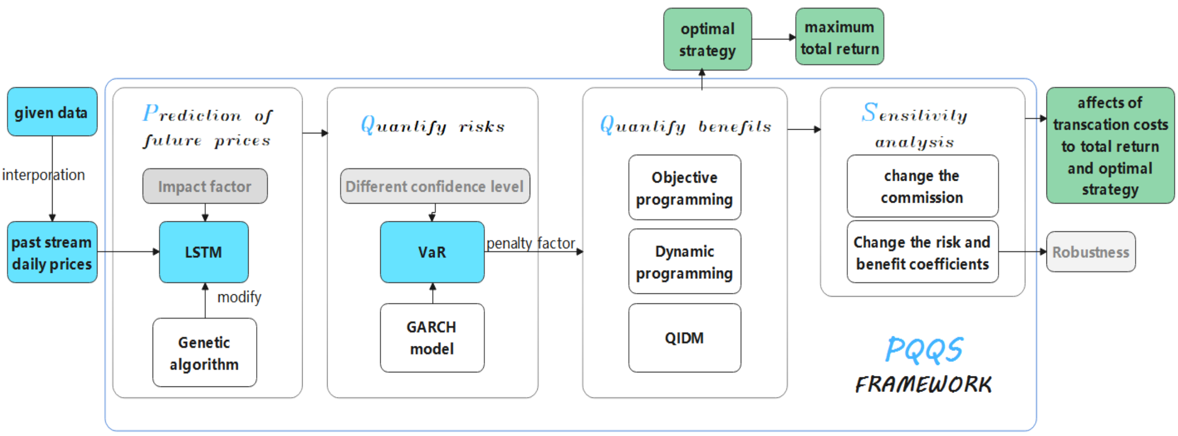


Figure 1. Model Framework

2 Assumptions and Justifications

Due to lack of necessary data and limitation of our knowledge, we make the following main assumptions to help us simplify our model and eliminate the complexity. These assumptions are the premise for our subsequent analysis.

Assumptions1: Market traders are all insatiable and rational, and their investment goal is to obtain the greatest possible return under certain risk conditions, or to reduce the risk as

much as possible under the condition of a certain rate of return. In other words, investors are risk-averse.
Justification: Traders always consider risk and return at the same time, and all want their transactions to have less risk and as high return as possible. However, according to the market law, risk and return are generally positively correlated. Therefore, our model needs to consider both risk and return, and combine them to make trading decisions, so as to obtain as much return as possible on the premise of low risk.

Assumptions2: There is no major change in economic policies during the investment period, and the economic development situation is relatively stable. That's to say, the future is predictable.
Justification: For short-term prediction, huge market or policy changes will have a significant impact on the prediction accuracy. In order not to make the model too complex, we do not consider the sharp price fluctuations caused by market and policy changes in short-term prediction. We only pay attention to the situation and trend of price changes over a period of time, so as to better predict and assess the risk and improve the accuracy of the model.

Assumptions3: The vast majority of individual differences of market traders e.g., economic status, educational level and trading preferences, are ignored.
Justification: We assume that traders do not trade in favor of bitcoin or gold, but make trading decisions based on their price trend and risk assessment, which is more in line with the reality of maximizing returns. In addition, we assume that there is no upper limit for bitcoin and gold transactions and non-integer transactions can be carried out (for example, buying 0.1 bitcoin), which will make our model more simplified and obtain better results and more accurate and reliable trading decisions.

Assumptions4: Neglect the discount rate of the capital. In this paper, we do not take the inflation into consideration and can calculate the total return measured in US dollars.
Justification: The appreciation and depreciation of the US dollar will affect the evaluation of total assets. In order to simplify the model without citing other data sets, we assume that the exchange rate of the US dollar has remained unchanged for a period of time, that is, there has been no appreciation or depreciation. On this basis, we can better convert the total assets at different times into US dollars for comparison, so as to better evaluate whether the suggestions given by our model for transaction decision-making are good enough.

Assumptions5: There is no limit to the amount of trading in the market.
Justification: The assumption is to ensure that our trading volume can be continuously changed, not discrete

3 Notations

Before we begin analyzing the problems, it is necessary to clarify the abbreviations and symbols that we will be using in our discussion. These are shown below in Table 1. The symbols which are not frequently used will be introduced once we use them.

Table 1. Notations used in this paper

Symbol	Description
s	Aggregate investment
k	Project number (k=1,2,3)
i	Days of investment (i=101,102....1826)
u_{ki}	The amount of investment allocated to project k on i_{th} day
p_{ki}	The price of project k_i
$p_{k(i+1)}$	The price of gold on day $k_{(i+1)}$
$g_{ki}(u_{ki})$	The income from investing u_{ki} in the k project
s_{ki}	The total amount of investment allocated to project k_i through project N_i
$f_{ki}(s_{ki})$	The maximum return from allocating S_{ki} to the project k_i to project N_i
α_k	The commission of project k
R_{ki}	The risk of project k_i

4 Data pretreatment

The provided datasets of Gold daily prices suffer from a bit data missing. Some of the missing data in that gold cannot be traded that day, some may be due to omissions during statistical process, which could undermine the integrity and the operability. To cope with the problem, we adopt Nearest Neighbour Interpolation (NNI), replacing the missing gold price with the nearest value. It must be admitted that although this method may not yield optimal results, it is reasonable and explicable. On the one hand, when the market is closed, the price of gold for the day has no effect on our return. On the other, there are few missing data due to statistical omissions, and the impact of filling data is negligible.

5 Future Prices Forecast Based on LSTM Model

5.1 The Structure of the Nested Two-layer LSTM Model

To predict the value of gold and bitcoin for the next few days on the trading day,we use Long and Short-Term Memory (LSTM)to model the VaRiation pattern of the gold and bitcoin.

LSTM model is a variant of recurrent neural network (RNN). It is well-suited to classifying, processing and making predictions based on time series data. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. The structure of our nested two-layer LSTM model is shown in Fig 2. The model is formed by three separate modules: input module, LSTM module and output module.

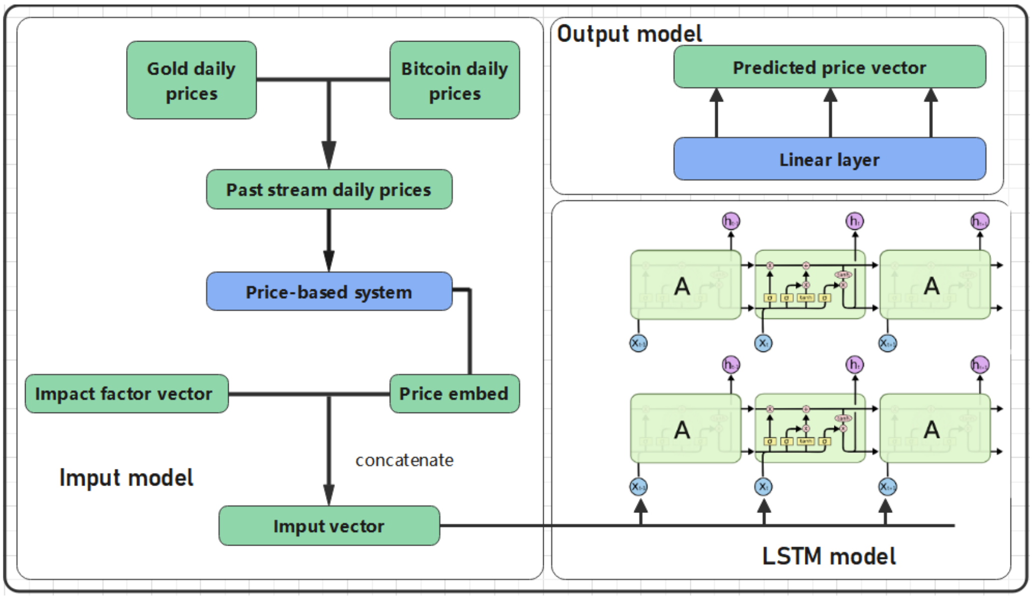


Figure 2. The structure of nested two-layer LSTM model

5.2 Input Module

For the market conditions at each time stamp, we first feed the daily prices of Gold and Bitcoin into the price-based embedding system to generate price embedding v_s which is represented as a 200-dimension vector. Next, we generate the input vector v_{in} for the nested 2-laywer LSDM model which features 200-dimension hidden size by integrating daily prices of Gold and Bitcoin up to the date of decision making with other potential impact factor, which is represented as a 3-dimension impact factor vector v_f.The detailed information about the impact factor vector v_f is explained in Table 2.

Table 2: Impact Factor Definition of vector v_f

Symbol	Description	Domain
x_1	The market is open or not	{0,1}
x_2	The impact rating of government economic policies	{1,2,3}
x_3	Current market stability	[0,1]

After concatenating all the impact factor thought of, the input vector for the LSTM can be formulated as:

$$\begin{cases} v_s = priceEmbed(Gold + Bitcoin) \in R^{200} \\ v_f = [x_1, x_2, x_3] \in R^3 \\ x = v_{in} = [v_s, v_f] \in R^{203} \end{cases} \tag{1}$$

5.3 LSTM Module

Here we explain the workflow of the one-layer LSTM unit:

$$\begin{cases} i = \sigma(w_{ii}x + b_{ii} + w_{hi}h + b_{hi}) \\ f = \sigma(w_{if}x + b_{if} + w_{hf}h + b_{hf}) \\ o = \sigma(w_{io}x + b_{ig} + w_{ho}h + b_{ho}) \\ g = \tanh(w_{ig}x + b_{ig} + w_{ho}h + b_{ho}) \\ c' = f * c + i * g \\ h' = o * \tanh(c') \end{cases} \tag{2}$$

We put the symbols that we use in the above workflow and their explanations in Table 3.

Table 3. Notations for one-layer LSTM

Symbol	Definition
$x \in R^{203}$	The concatenated input vector for the LSTM
$h \in R^{200}$	Hidden state, containing encoded information for the sequence flow
$c \in R^{200}$	Cell state, tracking dependencies between the elements in the input sequence
$i \in R^{200}$	Input gate, controlling the extent to which a new value flows into the cell
$f \in R^{200}$	Gathered input value from input x and current hidden state
$o \in R^{200}$	Output gate, controlling the extent to which the cell is used to compute outputs
w	The weight matrix for transactions
σ	The sigmoid function
b	The bias for transactions
tanh	The hyperbolic tangent function

Specifically, in our nested two-tier LSTM, one LSTM cell overlaps with another. We input the hidden state from the bottom LSTM into the top LSTM again, and use the hidden state from the top state as the input to the output module.

5.4 Output Module

As for the output module, we only need to input the hidden state of the upper LSTM into the linear layer to predict the price vectors, which have the same structure as v_{in} in the input module. The predicted value factor is shown below:

$$v_{predict} = w_{vh} + b \tag{3}$$

5.5 Results

Using our method stated above, we perform predictions on the daily prices of Gold and Bitcoin in the next three days. the results are listed in Figure 3 and Figure 4 respectively.

In order to improve network training speeds and thus peed up the efficiency of our model, we add Genetic Algorithm (GA) to accelerate the convergence speed.

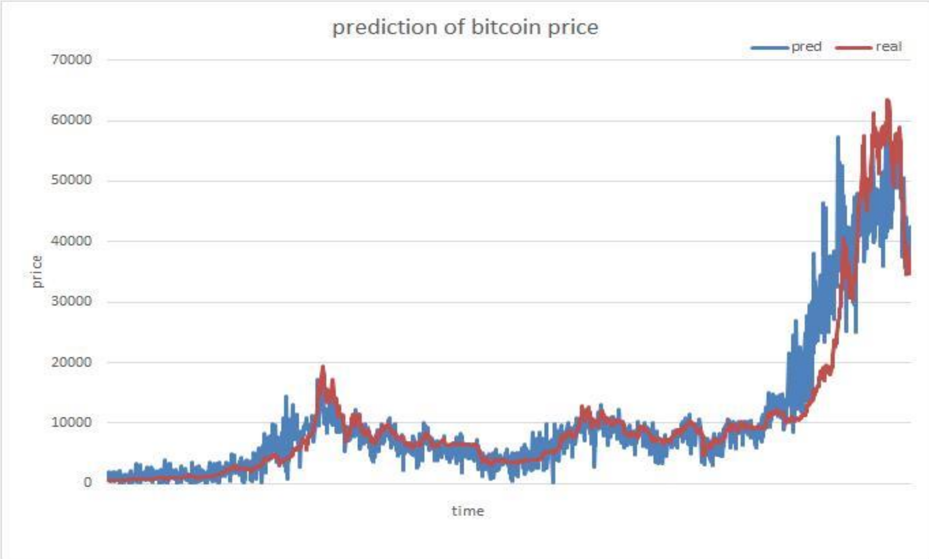


Figure 3. Predicted daily prices of Bitcoin based on LSTM

According to the predicted results shown above, the prices we predicted and the real roughly change in the same way. Given that our model can not accurately capture the real-time impact of economic policy and market conditions, the predicted results exist the time lag to some extent, that's why our model has a larger error in prediction at the time points when Bitcoin prices fluctuate markedly. Meanwhile, the result is also a true reflection of the complexity of the trading market, e.g., the influx of capital may cause huge fluctuations. That's to say however accurate the predicted values are, the risks of market trading are always objective.

Figure 4. Predicted daily prices of Gold based on LSTM

By comparing with Fig.3, we can find that LSTM works better when predicting the price of Gold. From an economic point of view, gold has a more stable value than bitcoin. Bitcoin is too volatile and its value is too easy to manipulate, so gold enjoys more actual prediction.

Through analysis of the results, we can find that Gold is a better safe-haven asset than Bitcoin.

6 Quantitative Investment Decision Model

6.1 Quantify Risks

6.1.1 VaR Calculation

Value at risk (VaR) is under a certain probability, the biggest possible loss of a financial asset or portfolio over a period of time in the future, which is widely used for risk control and performance evaluation[5].VaR is estimated to come under a certain confidence level and is targeted at market estimates under normal circumstances. Its unit is the amount, rather than the standard deviation or ratio.

The calculation formula of VaR is shown below:

$$VaR_t = P_{t-1}\phi^{-1}(a)\sqrt{h_t} \tag{4}$$

$$VaR_L = \mu + \frac{\sigma}{2}\left\{\frac{K+2}{SK} - \sqrt{\left(\frac{K+2}{SK}\right)^2 + 4\left[\frac{Z_\alpha\sqrt{(K+2)(K-SK^2+2)}}{|SK|} + 1\right]}\right\} \tag{5}$$

$$VaR_H = \mu + \frac{\sigma}{2}\left\{\frac{K+2}{SK} + \sqrt{\left(\frac{K+2}{SK}\right)^2 + 4\left[\frac{Z_\alpha\sqrt{(K+2)(K-SK^2+2)}}{|SK|} + 1\right]}\right\} \tag{6}$$

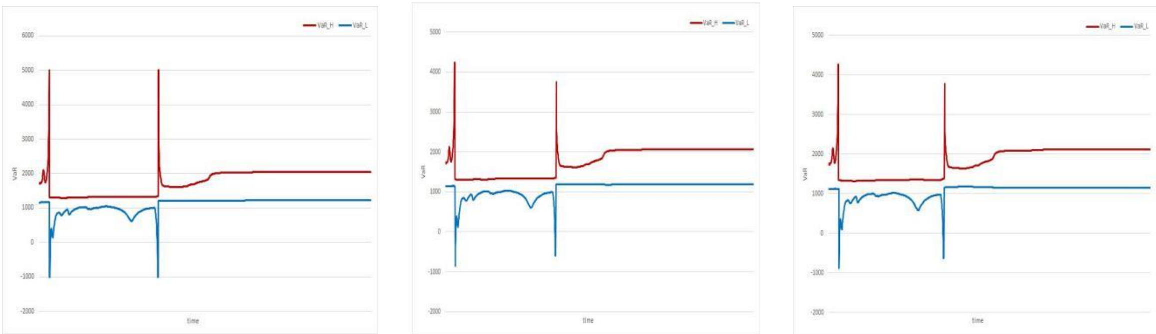
The table below describes the symbols appearing in the above formula.

Table 4. Notations for the above formula

Symbol	Description
VaR_L	The lower limit of VaR
VaR_H	The upper limit of VaR
μ	Mean value
σ	Standard deviation
K	Peak value
SK	Measure of skewness
Z_α	The quantile corresponding to the normal distribution α
α	probability

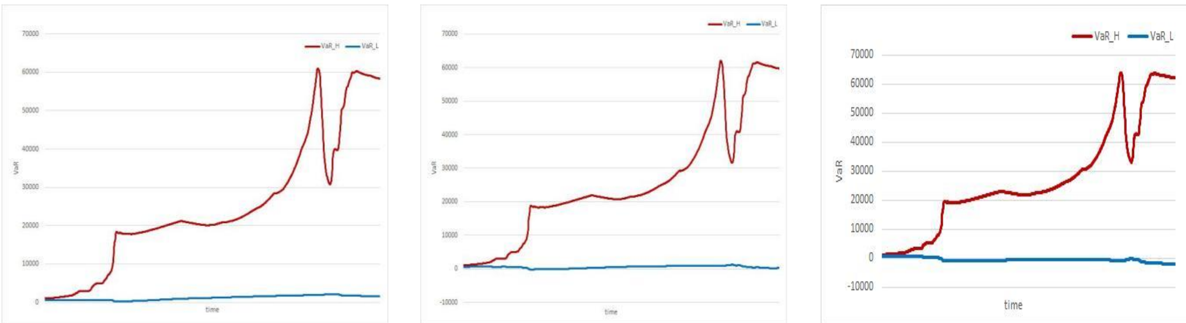
6.1.2 Results and Analysis of VaR Calculation

We use Matlab to calculate Var of Gold and Bitcoin with confidence interval of 90%, 95% and 95% respectively, as shown in Fig.5 and Fig.6. Given that the first 100 days were spent observing the market in that we lack data prior to November 9, 2016, we only calculated VaR after 100 days.



(a) 90% confidence interval (b) 95% confidence interval (c) 99% confidence interval

Figure 5. VaR of Gold price



(a) 90% confidence interval (b) 95% confidence interval (c) 99% confidence interval

Figure 6. VaR of Bitcoin price

Through the above diagram, we can find that VaR of Bitcoin is larger and more volatile, while the VaR of Gold is smaller and remains at a relative stable level. So, it's safely said that investing in bitcoin is riskier than investing in Gold. Comparing with Fig.5 and Fig.6, we also find that Value at risk is positively correlated with the value of the asset respectively. The high yield of the bitcoin market also brings greater value at risk. Just as many experts said that, Gold remains the traditional safe haven, unlike gold, bitcoin is a risky asset.

Moreover, at 99% confidence level, the VaR value based on GARCH model is more accurate, and surveys show that most people are risk averse. Therefore, it is more reasonable to choose the VaR value of at 99% confidence interval. In the QIDM model, we only consider the maximum value of VaR.

6.2 Quantitative Investment Decision

6.2.1 The Construction of QIDM Model

From the above, we have determined the risks during the investment. Next, we construct a model to better decide how to trade in the market.

At first, the simplest model we came up with for calculating the maximum returns was the Linear programming model, which is a two-objective linear program. But we will selectively invest $1000 in bitcoins and gold, according to the change of their value, we decide whether to continue to buy or sell them every day. The decisions we make not only depend on our predicted value of gold and bitcoin, but also rely on our holdings of gold and bitcoin on the previous day. Because of the special structure of this problem, we treat it as a multi-stage decision problem and solve it step by step.

So, considering the existence of the iterative process, we finally adopt the combination of dynamic programming and objective programming as the QIDM model. And QIDM model is essentially objective programming, and the implementation method is assisted by dynamic programming. Since we have get the standard of risks through VaR model, we make full use of the dynamic programming method and establish a model to solve the problem of how to reasonably allocate funds so that the portfolio can obtain the greatest benefits. Therefore, we establish the constraint conditions and objective function that meet the requirements of the topic, and calculate the income of initial investment of $1000 after five years through objective programming.

The formula used is as follows:

$$\begin{gathered} f_{ki}(s_{ki}) = max\{g_{ki}(u_{ki}) + f_{(k+1)i}(s_{(k+1)i}) - \alpha_k * u_{ki} - R_{ki}\}, \\ 0 \leq u_{ki} \ll s_{ki}\ , k = 1,2,3 \end{gathered} \tag{7}$$

$$f_{(N+1)i}(s_{(N+1)i}) = 0 \tag{8}$$

$$g_{ki}(u_{ki}) = u_{ki}/p_{ki} * p_{k(i+1)} \tag{9}$$

$$S_{(k+1)i} = S_{ki} + u_{ki} \tag{10}$$

We outline the model of our quantitative investment model with the following flowchart.

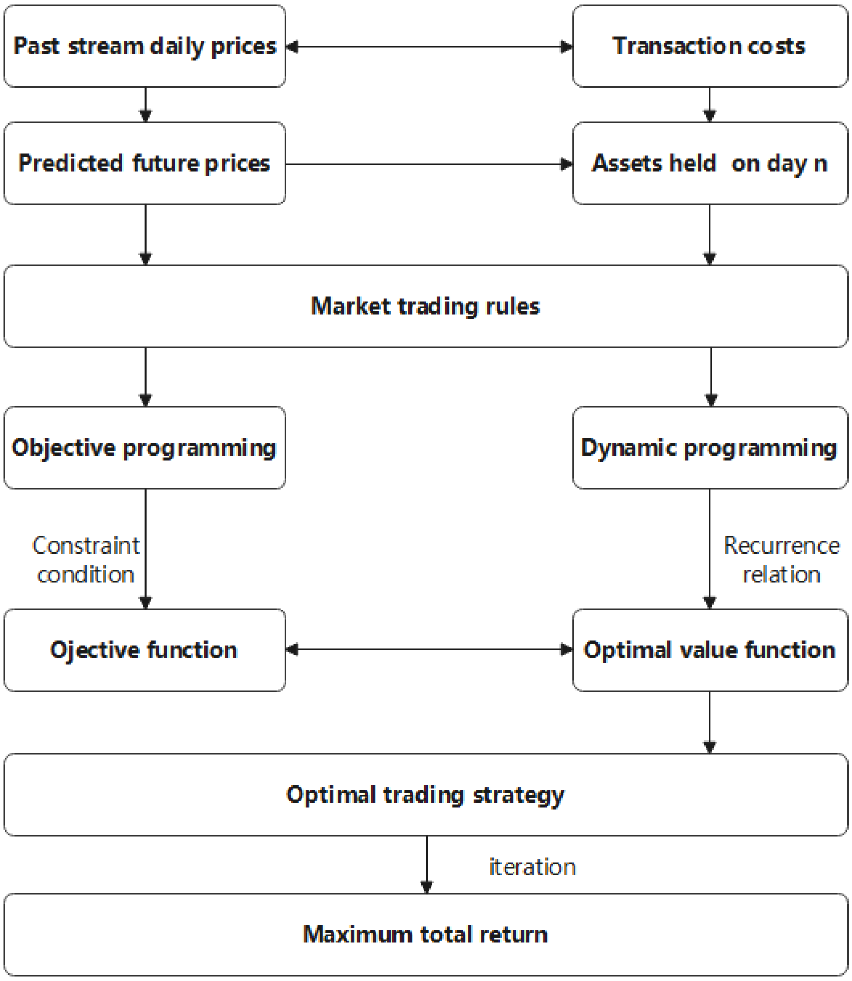


Figure 7. Flowchart of QIDM

It is necessary to add that our model takes into account the situation that the gold can not be traded on the day when the market is closed, and the obtained results show that the market closure does not affect the trading of gold very much, because the price of gold is relatively stable in general, and there is no need to conduct frequent trades, so the presence of a gold rest day won't have a big impact on the final result.

6.2.2 Model Results and Our Strategy

The total property predicted by our model is shown Fig.9.

Figure 8. the total return predicted by our model

As can be seen from figure 8, the curve stays at the stable level when there are no dramatic changes the prices of gold value and bitcoin value in the beginning. And then the return began to rise rapidly for the first time, but at the same time it grew less and less. And after a relatively stable period, it starts to go up in a sharper way. And then it changes in a various way, featuring larger fluctuation, but roughly matches the change of bitcoin value.

Several reasons may account for the phenomenon. The price of gold remains at a relatively stable level for a long time, so in our model we choose to guarantee a certain amount of gold to defend against risks and maintain relatively stable returns after comprehensively considering the benefits, risks and trading costs. Therefore, the fluctuation of the later income mainly comes from the violent fluctuation of the Bitcoin price. A sharp rise or fall in the price of bitcoin can bring about a dramatic change in the value of holding bitcoin. However, after adding VaR as a penalty factor, the results may indicate that traders are not suitable for frequent trading in the case of high price fluctuations. Therefore, the volatility of total assets is slightly less than that of Bitcoin while the trend of property is similar to trend of bitcoin value, in which gold value plays a role of cushion.

Through an in-depth analysis of Figure 8, we can also note a peak of total return about 90,000 yuan. By comparing the price fluctuations of bitcoin and gold predicted in Figure 3 and Figure 4 comprehensively, we find that the price of gold is near the peak, about \$2000.At the same time, the price of bitcoin is also at a sharp rising stage, and the risk brought by price fluctuations has not reached a very high level. In this case, it is perfectly reasonable to reach the total return to the maximum, which also indirectly demonstrates the effectiveness of our model.

Gold and Bitcoin holdings at the end of the five-year trading period, i.e., on October 9, 2021, are depicted in the following pie chart.

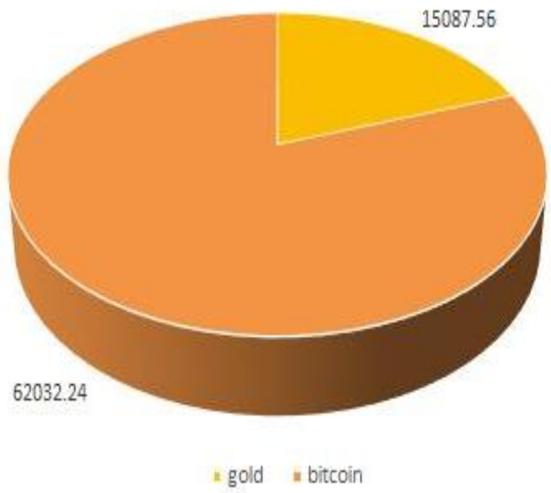


Figure 9. Holdings of gold Bitcoins at the end of the five-year trading period

As the pie chart depicts, the final $80,000 total return is mostly made up of gold and bitcoin. Specifically, since we do not consider the current return brought by depositing cash in the bank, the optimal strategy obtained by our model will invest as much cash as possible to obtain more returns.

At the same time, this pie chart is a good reflection of the respective characteristics of gold and bitcoin. The price of gold is stable, and it is impossible to obtain such high returns by buying gold in large quantities, but gold can be used as a safe-haven product and can play a role in storing wealth to a certain extent. Although Bitcoin's price volatility will bring a certain degree of risk, it also increases the possibility of obtaining high returns. Since our model can predict Bitcoin's price volatility well and can reasonably assess market risks, it will help us choose the right time to invest and get high returns. This is why our model can achieve high returns.

Based on the results obtained from our model, we give the following trading strategies:

• Accurately time your investments and buy variable assets when there is no sign of significant increase in VaR and their prices are on the rise.

• Maintain a good investment mentality and reduce the number of selling as much as possible on the premise that the price does not fall sharply.

•As a tool for investment and hedging, gold should be ensured a certain amount of investment to achieve the purpose of wealth storage when the price of Bitcoin fluctuates too much.

• When predicting the trough of Bitcoin price, the number of Bitcoin purchases should be increased to obtain more profits.

• If transaction costs rise, it is advised to cut the number of transactions.

6.2.3 Evidence for Optimal Strategy

Stock price prediction models can be divided into two categories: the traditional model based on statistical principles and the innovative prediction model based on neural networks and so on. However, the traditional model has fixed formula and limited ability to fit and predict the change trend of known data and unknown changes. The LSTM neural network model has been verified for a long time and its short-term prediction performance is excellent, and most researchers are inclined to neural network prediction, so we use the LSTM neural network to build forecasting model, and introduce the genetic algorithm to improve our model and make the model convergence faster and save the time of prediction.

For the establishment of risk assessment model, we adopt the VaR statistic which is commonly used in stock trading risk assessment and improve it to carry out risk assessment. VaR is more fully applied to the price data in the past than other statistics. It takes into account general statistics such as data fluctuation and expectation and combines them together to carry out risk assessment, making risk assessment more comprehensive and more conducive to making trading decisions based on risks. Compared with other risk assessment models, this model is the most suitable way for investment risk assessment based on past data is more accurate in risk assessment.

By combining risk with predicted return, we build a trading decision model. Through the objective programming, combined with the dynamic programming model, we get the best proportion of the impact of risk assessment and the forecast profit on the trading decision. To a certain extent, the trading profit can maximizes which proves that our model is the best decision model.

7 Sensitivity Analysis

In order to explore how sensitive the strategy to transaction costs, we change the transaction costs of gold and bitcoin by plus or minus 1% and plus or minus 5% and repeated the previous operation.

We find that the daily trading volumes of gold and bitcoin show the same trend as the trading results before the parameter change. In detail, when transaction costs rise, there will be fewer trading. What's worse, it will be more difficult for investors to adjust their portfolios in a timely manner based on forecast data to respond to changes in the market. In order to reduce transaction costs caused by frequent trades, investors can do nothing but choose to passively accept the relatively little losses caused by market changes. Therefore, the increase in transaction costs will reduce the ultimate maximum benefit to a certain extent. Conversely, the falling of transaction costs allows traders to increase the number of transactions. On the basis of accurately predicting the prices of gold and Bitcoin, they can choose to buy when the price is about to rise, and choose to sell when the price is about to fall, thus effectively avoiding losses and increasing profits. The trader's profit after the trade minus the transaction cost can still remain at a profitable level.

The results under different transaction costs are visualized below.

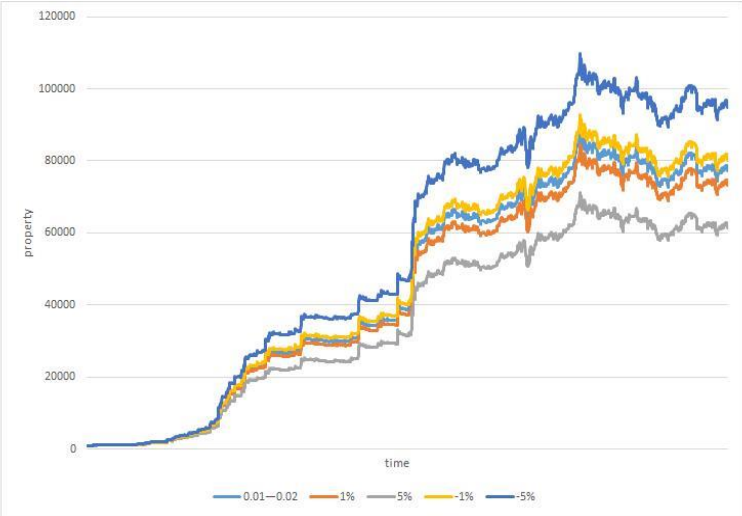


Figure 10. The maximum return under different transaction costs

We can conclude that changes in transaction costs have little effect on the optimal trading strategy. The increase in transaction cost will only reduce the number of trading and the final maximum benefit value in a certain amount, vice versa.

8 Model Evaluation and Further Discussion

8.1 Strengths

Technical Supporting: We use many theories and methods to support our work. And each one is used reasonably and properly. Thanks to these great theories and methods, can our model perform excellently.

Mathematical and Economical Model: Our models and parameters have direct economic meanings, while subjecting to mathematics laws at the same time.

Generalization and Visualization： Our proposed framework can freely be implemented to any data set e.g., stock price index from any online platforms. At the same time, data visualization technology is applied to interpret the original data, and the results are presented intuitively and concisely.

Suitable algorithm. In order to solve the problem of data prediction and improve the accuracy of data prediction, we have tried several algorithms and finally decide to choose the most suitable one. In addition, genetic algorithms are introduced to help LSTM neural networks converge faster.

8.2 Weaknesses

Limited accuracy： Since there are too many factors affecting the price of bitcoin and gold and we only rely on existing data for future price prediction, the accuracy of the prediction is limited to a degree.

Subjective: There are many subjective methods in the model and some of the indexes are put forward by our own experience and intuition, which are not very credible.

Local maxima or minima. Our model has considerable amount of parameters. Although it fits good to predict the future, it is inevitable that local maxima or minima is reached in predicting some factors.

8.3 Further Discussion

In spite of our model's success of gaining the best trading strategy, we still have a lot of work to do so as to optimize our model. On one hand, we will improve the LSTM algorithm and consider other important influencing factors, so that the data predicted by our model can achieve higher accuracy. In addition, people can gather more significant information and consider whether to buy gold or bitcoin from more angles.

On the other hand, when it comes to our QIDM, more factors related to risk assessment need to be explored, considered and incorporated into the model calculation. And due to game time restrictions, during the post-game time, we will read more literature and refer to the return and risk model of the analysis portfolio that scholars have explored. According to the actual situation of this case, we will build a more suitable decision model that can gain more benefits to help traders trade in the investment market.

9 Conclusion

The prices of gold and bitcoin change rapidly and unpredictably, making it important for traders to predict their prices, understand changing trends and assess the investment risks.

In our paper, we are prepared to present our insights and strategies to traders, helping them better trade gold and bitcoin. Firstly, we employ LSTM to predict the value of gold and bitcoin based on the real value in the past. We find that gold shows a smaller deviation between the predicted data and real date than bitcoin, due to its stability of value, while the great fluctuation results in a certain the difficulty of forecasting. Then, we make the most of VaR model to assess the risk of the trade. It is no doubt that investing in gold suffers from lower risk than bitcoin because the curve of gold value changes in a steadier way. After that, we take advantage of objective programming to obtain the maximum returns at certain risks we have predicted. Successfully, we draw the conclusion that we can gain 70 to 80 times our initial investment.

At last, we change the commission of gold and bitcoin to test our strategy's sensibility to transaction costs. We finally came to the conclusion that the change of transaction cost will not have a great impact on our optimal trading strategy, but will reduce or increase the number of transactions to a certain extent, and thus result in a certain change in the final total return. It should also be added that this effect tend to increase when transaction costs change significantly.

10 Memorandum to the Market Trader

Date: February 20, 2022
To: The trader
From: MCM Team # 2202981
Subject: Quantitative Portfolio Investment Insights and Recommendations

Based on the market price of gold and bitcoin given in the case, we are dedicated to develop an optimal strategy to maximize our return after five years with initial $1000 investment. To address the problem, we established a model called QIDM (Quantitative Investment Decision Model), which allows better allocation of your resources to help with decision-making process. Now, we are going to walk you through the development of our model.

Firstly, we adopted Nearest Neighbor Interpolation (NNI) to fill in the missing data of gold. Then our team used LSTM optimized by genetic algorithm to predict future market price of gold and bitcoin, and our model reaches a considerable accuracy in the test with the real data provided. At the same time, the introduction of VaR(Value at Risk) is to quantify the risks in the market. Finally, the objective programming is taken advantage of to achieve the maximization of total return on the basis of comprehensive consideration of risks and benefits.

The LSTM model makes reliable guesses at future price movements of gold and bitcoin. After visualizing the predicted results, it can aid market traders in their preliminary assessment of gains and losses. Comprehensively speaking, the price of gold fluctuates too little to generate high investment returns as well as deadly loss most of the time. The price of bitcoin is volatile, while being able to obtain higher returns, one must also consider the risks that need to be taken.

VaR can not only calculate the risk in advance, but also calculate the risk of a portfolio composed of multiple financial instruments, which cannot be achieved by traditional financial risk management. With Var added to the expected return as a penalty factor, market traders can effectively avoid risks as well as prevent the marginal effect of investment.

We successfully use QIDM model to calculate the maximum return with initial $1000 investment at the end of the five-year period, i.e.9/10/2021,and the maximum total return is about $80000.

By integrating the results obtained by the QIDM model with the impact of transaction costs on the optimal investment strategy, the proposed trading strategy is concluded as follows.

• Accurately time your investments and buy variable assets when there is no sign of significant increase in VaR and their prices are on the rise.

• Maintain a good investment mentality and reduce the number of selling as much as possible on the premise that the price does not fall sharply.

•As a tool for investment and hedging, gold should be ensured a certain amount of investment to achieve the purpose of wealth storage when the price of Bitcoin fluctuates too much.

• When predicting the trough of Bitcoin price, the number of Bitcoin purchases should be increased to obtain more profits.

• If transaction costs rise, it is advised to cut the number of trading.

Besides the aforementioned ability, the model is also capable of evolving itself when new information is given. On the latest circumstance, the predicted price, value-at-risk, and optimal investment strategies will be updated simultaneously.

It must also be admitted that although our model is very effective in trading decisions, the optimal values we calculated may not equal to the true global optimum because of the local optima and the lack of our knowledge.

We hope this model can serve as a valuable tool in our united effort to help with trading decision. After all, how to obtain greater benefits is not only the common wish of every participant in economic life, but also an important means to ensure the smooth operation of society and improve people's livelihood. If you have any further questions or problems regarding this model, please contact us and we will do whatever we can to explain or improve the model.

We are looking forward to your good news.

Yours Sincerely,
Team #2202981

References

[1] Wei Chen. Research on stock price forecasting model. *Research on Financial and Economic Issues*,2009*,* 7: 89-93.

[2] Xiaodong Xiang; Yaohuang Guo; Shangming Diao. Improvement of BP algorithm and its application in stock price prediction. Journal of Southwest Jiaotong University, 2001, 36.4: 425-427.

[3] Weiwei Xu; Feng Gao. Application of grey algorithm in stock price prediction. Computer simulation, 2007, 24.11: 274-276.

[4] Ying Fan. VaR method and its application in stock market risk analysis. Chinese Management Science, 2012, 3: 27-33.

[5]Drainville D. An Analysis of the Bitcoin Electronic Cash System[R]. Math.uwaterloo.ca,2012

Appendixes

Appendix 1

Introduce: var_calculate.py

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np


VAR_H=[]
VAR_L=[]
for i in range(100,1826,1):
        df = pd.read_csv(r'..\2022_Problem_C_DATA(1)\LBMA-
GOLD.csv',nrows=i)['gold']
    mean=df.mean()
    std=df.std()
    sk=df.skew()
    k=df.kurt()

        # za=1.2816 #90
    # za=1.6449#95
    za=2.263#99
    a=za*((k+2)**0.5*(k-sk**2+2)**0.5)/abs(sk)+1
       b=4*a+((k+2)/sk)**2
    c=b**0.5

        var_l=mean+(std/2)*((k+2)/sk-c)
    var_h=mean+(std/2)*((k+2)/sk+c)

        if var_h<5000:
        varh=var_h
    else:
        var_h=varh
    if var_l>-1000:
        varl=var_l
    else:
        var_l=varl

        VAR_H.append(var_h)
    VAR_L.append(var_l)
```

```
        ex  =  pd.DataFrame(VAR_L,  columns=['VaR_L'])
    ex.to_excel("gold_var_l99.xlsx",  index=False)

    ex  =  pd.DataFrame(VAR_L,  columns=['VaR_L'])
    ex.to_excel("gold_var_l99.xlsx",  index=False)

plt.figure(figsize=(16,7))

plt.plot(VAR_H,  'r',  label='VaR_H')
plt.plot(VAR_L,  'b',  label='VaR_L')

plt.legend()
plt.show()
```

Appendix 2

Introduce: data_visualization.py

```
import  pandas  as  pd

def  date_change(date):
    i  =  date.index('/')
        month  =  date[:i]
    j  =  date.rindex('/')
    day  =  date[i+1:j]
    year  =  date[j+1:]

        date_out='{0}-{1:0>2s}-{2:0>2s}'.format(year,month,day)
    return  date_out

path_b=r'2022_Problem_C_DATA(1)\BCHAIN-MKPRU.csv'
path_g=r'2022_Problem_C_DATA(1)\LBMA-GOLD.csv'

data_b=pd.read_csv(path_b)
```

```
data_g=pd.read_csv(path_g)

time_b=data_b['Date']
time_g=data_g['Date']

g_date=[]

for date in time_g:
    date_output=date_change(date)
    g_date.append(date_output)

        # list to dataframe
    df = pd.DataFrame(g_date, columns=['date'])

        # save to excel
    df.to_excel("g_date.xlsx", index=False)
```