Virtual currency trading strategy based on ARIMA and AHP-PSO

Hongru Song [1, *, #], Zijie Zhang [2, #]

[1] School of Economics and Management, Beihang University, Beijing, China, 100191

[2] School of Transportation Science and Engineering, Beihang University, Beijing, China, 100191

* Corresponding Author Email: s3158135873@163.com

[#]These authors contributed equally.

Abstract. As the price of virtual currency fluctuates greatly, precise prediction and appropriate trading strategies can bring investors best returns. This paper predicted the price of Ethereum and Bitcoin in the light of autoregressive integrated moving average model (ARIMA) and get a R^2 of 0.995 and 0.993 respectively, which indicates the model can yield reasonable predictions. Then their investment ratios are set to 0.88 and 1.12 respectively by analytic hierarchy process (AHP). Particle swarm optimization (PSO) is used to solve the daily revenue function formed by the predicted price and the current price. Finally, the paper compared the returns yielded by the PSO trading strategy optimized by AHP and the strategy without optimization. It can be concluded that the AHP has a possibility of 64.66 per cent to yield more returns when used.

Keywords: Virtual Currency, ARIMA, AHP, PSO

1. Introduction

In recent years, with the development of block chain, graphics cards and other software or hardware technologies, cryptographic virtual currency is gradually favored by the majority of investors [1]. In traditional markets such as stock market, sudden and sharp rises and falls in prices occur from time to time. This situation is even more evident in the virtual currency market [2].The basic idea for ARIMA model is to get several differences of non-stationary time to make it a smooth sequence, which has been widely applied. Researchers established ARIMA model to predict some stock prices of national stock exchanges, and the prediction effect is good [3].And The researchers optimized the workshop scheduling planning by using the particle swarm algorithm [4].On the basis of the above works, the paper predicted the price of Ethereum and Bitcoin in the light of autoregressive integrated moving average model (ARIMA). Then their investment ratios are set to 0.88 and 1.12 respectively by analytic hierarchy process (AHP). Particle swarm optimization (PSO) is used to solve the daily revenue function formed by the predicted price and the current price. Finally, precise prediction and appropriate trading strategies therefrom can bring investors best returns.

2. The basic funamental of ARIMA and AHP-PSO

2.1. Introduction to the principle of the ARIMA

The ARIMA model is a widely used statistical method for time series prediction, which is a class in temporal order Models capturing a set of different standard temporal structures in the column data. The lag of the stationary sequence in the prediction equation is called the "autoregressive" term, the lag of the prediction error is called the "moving average" term, and the time series requiring a difference to make it stationary is called the "integrated" version of the stationary sequence. The ARIMA model can be viewed as a "filter" that attempts to separate the signal from the noise and then extrapolates the signal to the future to obtain predictions. The ARIMA model is particularly suitable for fitting data showing non-stationarity. The ARIMA model can be represented as ARIMA (p, d, and q), the prediction formula of the model is as follows:

$$x_t = \phi_1 w_{t-1} + \phi_2 w_{t-2} + \cdots + \phi_p w_{t-p} + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q} \quad (1)$$

P is the autoregressive order, q is the moving mean order, and d is the number of differences done when time becomes stationary [5].

2.2. Introduction to the principle of the AHP-PSO

Hierarchical analysis method refers to a complex multi-objective decision problem as a system, according to the total goal, each layer sub-target, evaluation criteria until the specific plan sequence decomposition into different hierarchical structure, through the qualitative index fuzzy quantitative method to calculate the hierarchical single sort (weight) and total sort, and then solve the judgment matrix feature vector, each level, each element on the level of priority weight, and the method of merging the alternative scheme of the final weight. Hierarchical analysis is suitable for the target system with hierarchical interleaved evaluation index, and the target value is difficult to describe quantitatively.

Particle swarm algorithm, its full name is particle swarm optimization algorithm. It is a group collaboration-based search algorithm developed by simulating flock foraging behavior. Particle swarm algorithm belongs to the heuristic algorithm, which can intelligently optimize the solution of the planning model. Its basic idea is to find the optimal solution through the collaboration and information sharing among individuals in the group.

The particle swarm algorithm is initialized as a population of random particles (random solution) and then finds the optimal solution based on the iteration. In each iteration, the particle updates itself by tracking two extreme values: the first is the optimal solution found by the particle itself, which is called the individual extreme value, and the second is the optimal solution currently found by the entire population, which is called the global extreme value. You can also not use the whole population, but use a part of it as the neighbor of the particle, called local extremes.

Suppose that in a D-dimensional search space, there are N particles forming a community, where the i-th particle is represented as a D-dimensional vector:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{iD}), i = 1,2, \dots, N \quad (2)$$

The velocity of the i-th particle is expressed as:

$$V_i = (v_{i1}, v_{i2}, \dots, v_{iD}), i = 1,2, \dots, N \quad (3)$$

Also save the optimal solution found for each individual, and the optimal solution found by the whole community. The i-th particle updates its speed and position according to the following formula:

$$v_{id} = w \times v_{id-1} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (4)$$

$$x_{id+1} = x_{id} + v_{id} \quad (5)$$

Where P_{id} is the optimal solution known to the individual, p_{gd} is the known optimal solution of the population, w is the inertial weight, $c_1 c_2$ is the learning factor, and $r_1 r_2$ is the random number in the [0,1] range.

3. Result

The reference data of this article is the price of Bitcoin and Ethereum from November 1, 2019 to November 1, 2022. The data is from finance.sina.com.cn, and the currency unit is US dollars.

3.1. The establishment and analysis results of ARIMA virtual currency price prediction model

3.1.1 The establishment of ARIMA prediction model

In ARIMA (p, d, q), AR is "autoregressive" and the parameter p is the number of autoregressive terms. represents the number of lags in the time series data itself employed in the prediction model; MA is "sliding average", and the parameter q is the number of sliding average terms, which represents the number of lags of the prediction error used in the prediction model; d The number of differences (order) made to make it a stationary sequence. For investors, the future price of virtual currency is unknown, so the parameters p, q, d of the model cannot be obtained, but we can analyze bitcoin and ether price characteristics through previous prices, so we analyzed the change trend of Bitcoin and Ethereum prices from 2016 to 2019.

In order to obtain a stationary sequence, we respectively perform data difference on the price data of Ethereum and Bitcoin before, and perform the stability ADF test. The test results are shown in Table1 and Table2:

Table 1. Ethereum Price ADF Inspection Form.

ADF check list							
variable	Differential order	t	P	AIC	critical value		
					1%	5%	10%
eth	0	0.041	0.962	10463.31	-3.436	-2.864	-2.568
	1	-12.224	0.000***	10452.605	-3.436	-2.864	-2.568
	2	-15.022	0.000***	10572.134	-3.436	-2.864	-2.568

***, **, *represent the significance levels of 1%, 5% and 10%, respectively

Table 2. Bitcoin Price ADF Inspection Form.

ADF check list							
variable	Differential order	t	P	AIC	critical value		
					1%	5%	10%
bit	0	-1.091	0.719	9990.439	-3.436	-2.864	-2.568
	1	-11.958	0.000***	9981.375	-3.436	-2.864	-2.568
	2	-14.582	0.000***	10063.21	-3.436	-2.864	-2.568

***, **, *represent the significance levels of 1%, 5% and 10%, respectively

According to the ADF test results, it can be determined that the prices of both Ethereum and Bitcoin are differentiated once to obtain a stationary sequence, that is, the d value of both ARIMA models is 1.

Next, we will analyze the autocorrelation of the prices of Bitcoin and Ethereum, and draw autocorrelation graphs and partial autocorrelation graphs of the first-order difference data of the prices of two virtual currencies. We optimized the parameters of the ARIMA model of both currencies and obtained that the p-value is 2 and the q-value is 3 in the ARIMA of Ethereum; in the ARIMA model of Bitcoin, the p-value is 5 and the q-value is 0.

Through data difference and autocorrelation analysis, it is concluded that ARIMA model for forecasting Ethereum price is ARIMA (2, 1, 3), and ARIMA model for forecasting Bitcoin price is ARIMA (5, 1, 0). In order to verify the accuracy of model parameters and the rationality of the model, the effect of the model is tested. The test results are shown in Table3 and Table4:

Table 3. Test Table for Effectiveness of Ethereum Price Forecast Model.

ARIMA(2,1,3)check list		
term	symbol	value
Sample size	Df Residuals	1089
	N	1096
Q statistical quantity	Q6(P value)	0.054(0.816)
	Q12(P value)	0.372(0.999)
	Q18(P value)	0.762(1.000)
	Q24(P value)	1.211(1.000)
	Q30(P value)	2.01(1.000)
Information criteria	AIC	10571.676
	BIC	10606.666
goodness of fit	R^2	0.991

***, **, *represent the significance levels of 1%, 5% and 10%, respectively

According to Table3 above, from the analysis of Q statistics results, it can be concluded that Q6 is not significant at the level, the assumption that the residual error of the model is a white noise sequence cannot be rejected, and the goodness-of-fit R^2 of the model is 0.991, the model performance is excellent, and the model basically meets the requirements.

Table 4. Test Table for Effectiveness of Bitcoin Price Forecast Model.

ARIMA(5,1,0)check list		
term	symbol	value
Sample size	Df Residuals	1089
	N	1096
Q statistical quantity	Q6(P value)	0.892(0.345)
	Q12(P value)	38.967(0.000***)
	Q18(P value)	38.967(0.000***)
	Q24(P value)	38.967(0.003***)
	Q30(P value)	38.967(0.028**)
Information criteria	AIC	10243.268
	BIC	10278.258
goodness of fit	R^2	0.993

***, **, *represent the significance levels of 1%, 5% and 10%, respectively

According to Table4 above, from the analysis of the Q statistic results, it can be obtained that Q6 does not show significance at the level, and the assumption that the residual of the model is a white noise sequence cannot be rejected, and the goodness-of-fit R^2 of the model is 0.993, the model performance is excellent, and the model basically meets the requirements.

3.1.2 Analysis of experimental results

Through the analysis of the previous virtual currency prices, we determine the values of parameters p, d, q, and verify the rationality of the model, and then we use the ARIMA (2,1,3) model obtained earlier ARIMA (5, 1, 0) model, respectively on November 1, 2019 Predict the price of Ethereum and Bitcoin in the future. The comparison between the predicted price and the actual price is shown in Figure 1 and Figure 2 below:

Figure 1. Bitcoin forecast vs. real price chart.

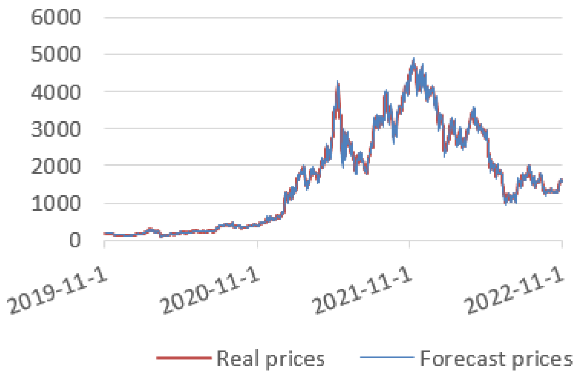

Figure 2. Ether forecast vs. real price chart.

From the results in Table5 and Table6, it can be seen that the ARIMA price prediction model established for Ethereum and Bitcoin has a good prediction effect.

Table 5. Ether price prediction performance.

Ethereum price forecast effect	
Steady R^2	0.511
R^2	0.995
RMSE	1285.452
MAP	2.683

Table 6. Bitcoin price prediction performance.

Bitcoin price forecast effect	
Steady R^2	0.448
R^2	0.993
RMSE	110.953
MAP	4.022

3.2. AHP Model-PSO Establishment and analysis results

3.2.1 The establishment of AHP-PSO Trading strategy mode

If the transaction is only conducted according to the price of the day and the price of the next day obtained from the prediction model, the transaction is risky due to the limited information. Therefore, in addition to the forecast data, it is also necessary to consider the volatility of the transaction income, the growth trend, and the transaction fees when building the decision-making model.

To better determine the weight of investment, we use the Analytic Hierarchy Process to determine the proportion of Bitcoin and Ethereum invested in transactions [6].

In this model, the target layer is the optimal investment strategy, the criterion layer is the volatility of returns, growth trend, transaction fees, etc. The solution layer is Bitcoin and Ethereum.

In the hierarchical evaluation model, the volatility of returns is the most important, followed by transaction fees, and finally the growth trend, and we construct the criterion layer judgment matrix in this order, as shown in Table7:

Table 7. Criteria layer judgment matrix.

target	Volatility of earnings	Transaction fees	Growing trends
Volatility of earnings	1	7	9
Transaction fees	0.143	1	3
Growing trends	0.111	0.333	1

The weight calculation results of the analytic hierarchy method show that the weight of the volatility of earnings is 78.539%, the weight of transaction fee is 14.882%, and the weight of the growth trend is 6.579%.

Table 8. The consistency test of analytic hierarchy.

Results of consistency inspection				
Maximum feature root	CI value	RI value	CR value	Results of consistency inspection
3.08	0.04	0.525	0.076	Pass

The calculation results of the analytic hierarchy process show that the maximum feature root is 3.08, and the corresponding RI value is 0.525 according to the RI table, as shown in Table8, so CR=CI/RI=0.076<0.1, which passes the one-time test.

By using the GARCH family model, we reached the conclusion that Bitcoin is the most vulnerable and Ethereum is the strongest in the face of shocks [7].

At the same time, considering the transaction fees and growth trend of Bitcoin and Ethereum, we construct the following scheme layer judgment matrix, as shown in Table9:

Table 9. Scenario layer judgment matrix.

	Bitcoin	Ethereum
Transaction fees	0.5	0.5
Volatility of earnings	0.143	0.857
Growing trends	0.75	0.25

Based on the single ranking of indicator levels and the total ranking of scheme levels, for investment strategies, Ethereum quantifies with a score of 1.047, Bitcoin has a quantization score of

0.833. Based on the obtained weight ratio, we can set the transaction weights of Bitcoin and Ethereum to 0.88 and 1.12, respectively.

Based on the above conditions, we build a linear programming model. To better describe the model, we set these variables:

z1: Ethereum holdings before trading
z2: Bitcoin holdings before trading
x1: Ethereum holdings after trading
x2: Bitcoin holdings after trading
m1: today's Ethereum prices
m2: today's Bitcoin prices
n1: the next day's Ethereum prices
n2: the next day's Bitcoin prices

Where the objective function is:

Daily return = Ethereum's weight in the investment * (the next day's Ethereum price / today's Ethereum price) * Ethereum holdings after trading + Bitcoin weight in investments * (the next day's Bitcoin price / today's Bitcoin price) * Bitcoin holdings after trading - Fees incurred by transactions

$$\begin{gathered}\max Z = 1.12 * \frac{n_1}{m_1} * x_1 + 0.88 * \frac{n_2}{m_2} * x_2 \\ -0.01 * \frac{n_1}{m_1} * |x_1 - z_1| - 0.01 * \frac{n_2}{m_2} * |x_2 - z_2|\end{gathered} \tag{6}$$

For this objective function, we set the following constraints:

(1) Due to the limited principal, the purchase and sale volume of Bitcoin and Ethereum on the day shall not exceed the holding amount of the previous day:

$$-z_1 - z_2 < x_1 + x_2 < z_1 + z_2 \tag{7}$$

(2) The sales volume of Bitcoin and Ethereum on the day shall not exceed the respective holdings of the previous day. Both Ethereum and Bitcoin held at the time of the transaction and after the transaction are greater than or equal to 0:

$$\begin{cases} x_1 > 0 \\ x_2 > 0 \end{cases} \tag{8}$$

(3) If you want to buy a certain amount of a coins, you need to sell a certain amount of B coins, so the purchase amount of Bitcoin and Ethereum on the day must not exceed the amount held by the other party the previous day:

$$\begin{cases} x_1 < z_2 \\ x_2 < z_1 \end{cases} \tag{9}$$

(4) Since the transaction of Bitcoin and Ethereum requires a certain amount of handling fees, the transaction is carried out when the income obtained after calculating the rate of return is higher than the procedure fee. That is, the profit obtained after buying or selling on the same day is greater than the commission generated in the same day transaction (the commission is assumed to be 1% in this investment strategy):

$$\begin{cases} 0.01 <= \dfrac{n_1}{m_1} - 1 \\ 0.01 <= \dfrac{n_2}{m_2} - 1 \end{cases} \tag{10}$$

3.2.2 Analysis of experimental results

In this model, the opposite number of the objective function is taken as the fitness degree in the particle swarm algorithm (the value of evaluating the strength and disadvantage of particles) [8], and the minimum value of the opposite number of the objective function and its corresponding daily trading volume of Bitcoin and Ethereum are obtained through the algorithm, so as to maximize the final return.

In the actual algorithm, we confirm the actual return by updating the predicted currency price to the actual currency price, and continue to predict the subsequent currency price at the actual price, so as to guarantee the accuracy of the daily data and the final return.

Following this process, through the established circular decision model, we can derive the final holdings and maximum gains of Bitcoin and Ethereum. After the initial \$1000 decision through the model, the total asset value is now about \$4685.3. The relationship between total asset value and time is shown in Figure3.

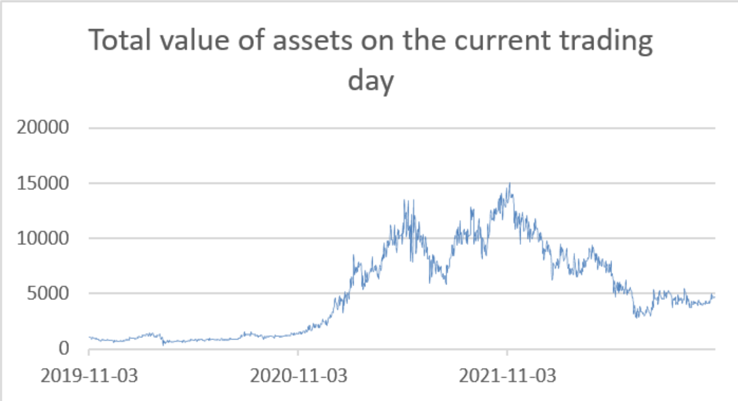

Figure 3. Total asset value.

Arithmetic rate of return and geometric rate of return are important indicators for evaluating the investment return of a portfolio over a period of time [9]. Suppose an investor buys an asset at 0 at a price of 0, and then records the price of the asset at regular intervals, respectivelyP_0, P_1, P_2, P_3.... Then the arithmetic rate of return for a single period in the [t-1, t] time period is:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1 \tag{11}$$

The multi-period arithmetic yield for the [t-k, t] time period is:

$$\begin{aligned} R_t[k] &= \frac{P_t - P_{t-k}}{P_{t-k}} = \frac{P_t}{P_{t-1}} \times \frac{P_{t-1}}{P_{t-2}} \times \cdots \times \frac{P_{t-k+1}}{P_{t-k}} - 1 \\ &= \prod_{i=0}^{k-1}(1 + R_{t-i}) - 1 \end{aligned} \tag{12}$$

In this model, the final multi-period arithmetic yield is 368.5309563%, the highest single-period arithmetic yield is 141.4697664%, and the average single-period arithmetic yield is 0.70270113%.

Geometric yields also include single-period geometric yields and multi-period geometric yields. Assuming that r is the interest rate over the [t-1, t] time period, and m represents the number of times interest has been compounded in that time period, then the geometric rate of return for a single period in the [t-1, t] time period is:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}) \tag{13}$$

The multi-period geometric rate of return for the [t-k, t] time period is:

$$r_t[k] = \ln\left(\frac{P_t}{P_{t-k}}\right) = \ln\left(\frac{P_t}{P_{t-1}} \times \frac{P_{t-1}}{P_{t-2}} \times \cdots \times \frac{P_{t-k+1}}{P_{t-k}}\right) = \sum_{i=0}^{k-1} r_{t-i} \tag{14}$$

In this model, the final multi-period geometric yield is 154.4431989%, the highest single-period geometric yield is 88.15740885%, and the average single-period geometric yield is 0.141172942%.

In the decision-making model, if the data is only obtained from the prediction model is used for trading, there is a greater risk in the trading. Therefore, in addition to the forecast data, other factors should be considered when building the decision model. In order to get a more scientific investment strategy, we use the analytic hierarchy process to analyze the weight of Ethereum and Bitcoin, and take this as one of the basis for modeling.

In order to verify the necessity and effectiveness of AHP in the modeling process, we have established a new decision-making model, in which the influence of the weight of two currencies on the transaction decision is deleted, so as to study the final income of the model without AHP.

The final total asset value obtained by solving the new model is about $4672.19, which is lower than the original model using the analytic hierarchy process. It can be seen intuitively from Figure4 that, in most cases, the income of the original model is higher than that of the new model without AHP during the period from November 1, 2019 to November 1, 2022.

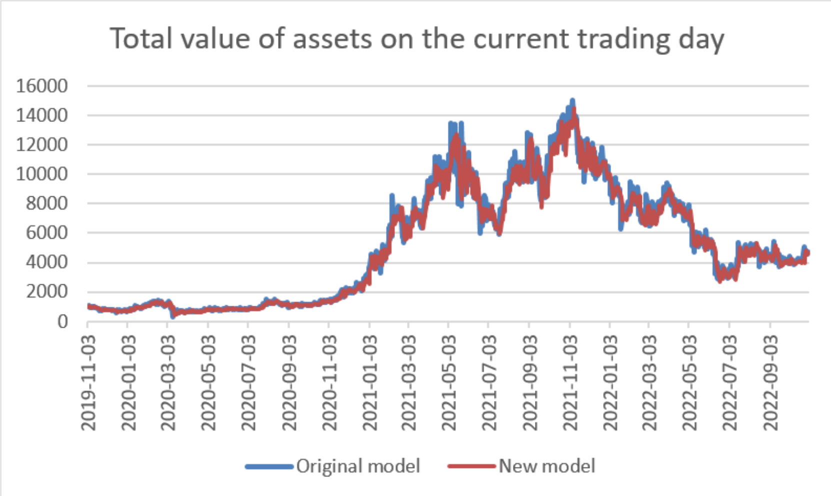

Figure 4. Comparison of the total asset value of the original model with the new model.

According to the data analysis, in 64.44% of the cases, the income of the original model is higher than that of the new model. Therefore, it is necessary to take AHP as one of the bases of investment in the transaction decision-making model.

Due to the influence of internal market factors, macroeconomic factors and policy factors, the price of virtual currency tends to have short-term fluctuations. Facing the rapidly changing market, we need to study whether the transaction decision model can stably give the best decision results. Therefore, we choose the service charge parameter to analyze the sensitivity of our model.

In previous research, we assumed fees for Ethereum and Bitcoin to be 1% of trading volume. To study the changes in the model decision-making process and results, we chose different fees in the new model, i.e. 1%, 2%, 3% and 5% for Bitcoin and Ethereum, respectively. While exploring the sensitivity of our trading strategy to commissions, we also hope to verify the stability of the model.

We substitute different transaction fees into the model and the final payoff of them is $4685.31, $4577.89, $4483.59, $4294.98 respectively.

Figure5 visually shows that changes in fees affect the final payoff of our model, and the fee is negatively correlated with the final return. As the commission decreases, the final return of our model increases, which is obviously in line with the general law of market trading [10].

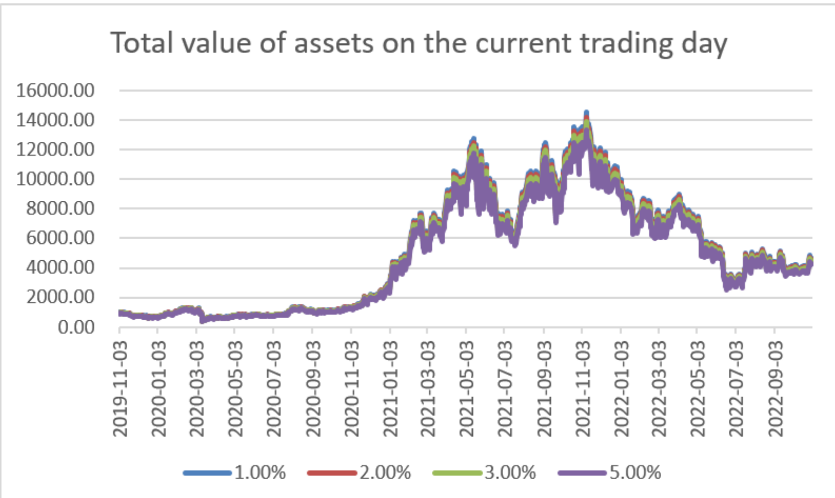

Figure 5. Comparison chart of the total asset value when the commission changes.

At the same time, although the change of the fee affects the final income result, it can be seen from the picture that different fees have little impact on the income. The income is stable within a certain range, indicating that the stability of the model is strong, and it can provide a better trading decision in the face of different environments.

4. Conclusions

In this paper, we establish an ARIMA model to predict the prices of Ethereum and Bitcoin. Compared with the actual price, the model has a good fitting effect, indicating that the prediction model can accurately help investors grasp the price fluctuations of the two currencies. At the same time, we also built a decision model to help investors get as much profit as possible in their decision-making. Finally, in the course of three years of trading, we helped investors obtain a total asset of about $4685.31 through the initial $1000, with a yield of 368.5%. During the period from November 1, 2019 to November 1, 2022, the highest single period arithmetic yield was 141.4697664%, and the average single period arithmetic yield was 0.70270113%.

To verify the effectiveness of analytic hierarchy process in the decision model, we build a new model to compare it. The results show that in 64.44% of the cases, the income obtained by adopting AHP as one of the decision-making bases is higher than that of the ordinary model without AHP.

In addition, in order to ensure that the transaction decision model can stably give the best decision results under different market environments, we choose the service charge parameter to analyze the sensitivity and stability of our model. The results show that the commission is negatively related to the final income, which is in line with the general law of market transactions, and different commissions have little impact on the income. The income is stable within a certain range, and the model has strong stability. In the face of different environments, it can provide a better transaction decision.

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