Dynamic Rebalancing of Cryptocurrency Portfolio Based on Forecasted Technical Indicators and Random Forest Method

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Abstract

The article focuses on the dynamic rebalancing of cryptocurrency portfolio. It presents a novel approach that leverages machine learning, specifically the Random Forest method, to predict future trends in the cryptocurrency market and adjust portfolio composition accordingly.

A key aspect of this research lies in its use of forecasted technical indicators, such as the Moving Average Convergence/Divergence Histogram (fMACDH%), modified for this specific application. These indicators are used to determine the best moments for buying or selling assets, aiming to maximize returns while minimizing risks.

The proposed dynamic rebalancing model, which adjusts portfolios according to the predicted movements of technical indicators, can notably improve portfolio performance. This is evidenced by substantial returns on investment in test cases. The research also highlights the importance of selecting appropriate model parameters, as these greatly influence the volatility and overall performance of the portfolio.

Keywords [1]

Portfolio rebalancing, cryptocurrency, technical indicators, Random Forest

1. Introduction

Since the introduction of Bitcoin in 2009, cryptocurrency has attracted a lot of interest among investors due to its dynamic nature and great potential for high returns. At the same time, its volatility provides both the opportunity for large gains and can lead to the loss of a significant amount of capital. Since the emergence of cryptocurrencies, many portfolio optimization strategies have been proposed, which are usually based on traditional investment approaches, such as the Markowitz portfolio theory.

However, given the peculiarities of cryptoassets, in particular their high volatility and low correlation with traditional assets, there is a need for new, adapted approaches to the optimization of cryptocurrency portfolios. One such approach is dynamic portfolio optimization based on machine learning methods. This approach allows for predicting future trends in the cryptocurrency market and adjusting the portfolio to these forecasts [1].

A significant amount of modern research is devoted to the technical aspect of financial technologies. Works [2]-[7] are devoted to the application of cloud technologies, blockchain, cryptography and other modern technologies in finance. These articles reveal the essence, characteristics, advantages, and disadvantages of these technologies, as well as their opportunities to improve the efficiency, security, transparency, and innovation of financial processes, such as e-commerce, asset management, mergers and acquisitions, supply chain tracking, dynamic programming, and others . So, for example, works [2], [3], [8] consider the use of cloud technologies in e-commerce to ensure the fast, flexible, and reliable provision of services, such as customer relationship management, supply chain management, content management, product management information, and others. One of the methods used in solving complex optimization problems in financial models with transaction costs is dynamic programming [2]. The article [6] investigates the use of cloud technologies for dynamic portfolio optimization using inverse covariance clustering to account for changes in the structure of dependencies between assets.

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Articles [1], [8]-[22] belong to a group of articles examining cryptocurrency markets from different perspectives. These articles examine concepts such as investor behavior, volatility, risk, regulation, and innovation to analyze the features and prospects of cryptocurrencies as a new type of financial asset. So, in particular, in the article [10], the author examines the issue of how social media, in particular Elon Musk's tweets, affect the prices and volumes of cryptocurrency trading. Duan and Urquhart [16] explore the advantages and disadvantages of stablecoins, which are tied to traditional currencies or other assets, to ensure stability and liquidity in cryptocurrency markets. The authors of the article [1] investigate the opportunities and challenges created by decentralized finance (DeFi), which uses blockchain and smart contracts to provide financial services without intermediaries.

No less interesting and useful for our research work [19], [23], [24] devoted to the issue of researching methods and tools of technical analysis that can be used for forecasting and trading of cryptocurrencies. Also, in these works, attention is paid to the effectiveness of the studied methods.

An important issue for research is the comparison of cryptocurrency assets with traditional assets such as gold, stocks, and bonds, in terms of volatility, connectedness, risk, and profitability [11], [15], [22]. The authors of the paper [20] draw attention to the risks and threats to cryptocurrency markets from attackers who can use cryptographic attacks, forgeries, double spending, 51% attacks, and others. At the same time, in works [9], [14], [17], [21], the authors focus on the prospects of development and innovation in cryptocurrency markets, taking into account technological, economic, social and legal factors. Article [25] is devoted to modeling the volatility of currency pairs and indices using complex networks. The authors of the article use the method of complex networks to analyze the dynamics of volatility of currency pairs and indices, as well as to identify connections between them.

Article [26] is devoted to the issue of using neural networks for simulating cryptocurrency exchange rates. The authors of the article use different types of neural networks, such as multilayer perceptron, recurrent neural network, and deep neural network, to forecast the exchange rates of cryptocurrencies such as Bitcoin, Ethereum, Litecoin, Ripple, and others. The paper compares the neural network approach with traditional forecasting methods, such as ARIMA, ETS, SVM, and others.

Articles [23], [27], [28] examine financial assets using technical analysis, machine learning, portfolio optimization, and risk-return analysis. These articles use concepts such as trends, momentum, volatility, correlation, diversification, trailing edge, mean-variance analysis, technical analysis indicators, gradient boosting, genetic algorithms, simulated annealing, and others to analyze, value, and manage financial assets. The authors of these works consider in detail the issue of using technical analysis indicators, such as the MACD histogram, to identify trends and changes in market momentum [23], [24], [27]. An important study related to the use of cloud technologies for dynamic portfolio rebalancing with lag-optimized trading indicators using SeroFAM and genetic algorithms to increase returns and reduce risk [7].

The purpose of this work is to build a model for rebalancing the portfolio of cryptoassets based on the forecasted indicators of technical analysis using the Random Forest method. Based on the initial optimal portfolio of cryptocurrencies, it is proposed to dynamically rebalance the portfolio using the comparison of the forecasted percentage MACD histogram with the threshold values.

2. Methods

One of the key concepts of technical analysis is the definition of trends. Technical analysis assumes that prices usually move in trends. The trend can be upward (bullish), downward (bearish) or horizontal (sideways). Investors can use various tools such as trend lines, moving averages, and indicators to identify trends [23]. Technical indicators are mathematical calculations that use price and/or volume to predict future price movements. They can be used to determine trends, volatility, momentum, etc.

A moving average is used to detect trends, it determines the average price of an asset over a certain period. The exponential moving average (EMA) is calculated by the formula:

$$EMA_t = \frac{2}{N+1} \cdot P_t + \left(1 - \frac{2}{N+1}\right) \cdot EMA_{t-1}, \tag{1}$$

where t – the period number, P_t – the asset price, N – the number of periods for which the EMA is calculated.

Two periods are traditionally defined: 12 for the short-term EMA; and 26 for the long-term EMA.

Moving Average Convergence/Divergence (MACD) is calculated as the difference between the short-term and long-term EMA. MACD is a trend-following tool that uses moving averages to determine the momentum of a stock, cryptocurrency, or other trading asset. This indicator tracks price events that have already occurred and thus falls into the category of lagging indicators (which provide signals based on past price action or data). MACD can be useful for measuring market momentum and possible price trends and is used by many traders to identify potential entry and exit points. MACD consists of three elements moving around the zero line:

- The MACD line helps to identify an upward or downward momentum (market trend). It is calculated as the difference between EMA(short) and EMA(long).
- The signal line is defined as the EMA of the MACD line (usually a 9-period EMA). Combined analysis of the signal line with the MACD line can be useful for identifying potential reversals or entry and exit points.
- Histogram (MACDH) gives a graphical representation of the divergence and convergence of the MACD line and the signal line. The histogram is equal to the difference between the MACD and its signal line. MACDH can be used as an early indicator of trend reversals in the price momentum of the underlying security [24].

However, MACDH is sensitive to "sawtooth effects" [27], i.e. minor fluctuations in the price lead to frequent and significant fluctuations in the value of the indicator. The consequence of this effect is an excessive number of trades, which increases the cost of commissions and decreases the return on investment (ROI). To solve the problem of minor fluctuations near the zero axis, a modification of this index was introduced, which is denoted MACDH% and is calculated according to the formula:

$$MACDH\% = \frac{MACDH}{0.5(EMA_{12} - EMA_{26})} \cdot 100\%. \tag{2}$$

Since the MACDH% index is in the form of percentages, it allows investors to compare MACDH% values between different investment assets. All of these technical analysis tools can help identify potential entry and exit points for trading, which is important for reallocating resources between portfolio assets in dynamic programming. They are best used in combination with each other, along with fundamental analysis or machine learning elements [19]. One of the methods of such synthesis was proposed by L. L. X. Yeo et al. [7]. The authors introduced the forecasted MACDH% (fMACDH%), which is based on the so-called "forecasted" analogs of the EMA and MACD indicators.

The forecasted EMA (fEMA) is calculated by the formula:

$$fEMA_t = w \cdot \tilde{F}_{t+1} + (1 - w) \cdot EMA(MACDH\%)_t, \tag{3}$$

where t – the period number, $\tilde{F}_{t+1}$ – the MACDH% value of the next period, w – a weighting factor that takes values from 0 to 1.

Further calculations of the forecasted indicators of the MACD group (fMACD) are performed in the same way as described above but with the replacement of components with forecasted counterparts. This modification allows for the reduction of the delay effect of the aforementioned technical indicators [7]. For dynamic rebalancing of the portfolio, we suggest applying the following algorithm, which will be called for convenience "Proportional dynamic rebalancing of the portfolio according to the Alpha-Beta fMACDH% criterion" (**Error! Reference source not found.**). For each cryptocurrency in each period, the model compares the corresponding value of fMACDH% with two parameters: Alpha and Beta, where Alpha is greater than or equal to Beta. If the value of fMACDH% is less than Beta, then all coins of the corresponding cryptocurrency are sold and the amount of money received from the sale is calculated. The fMACDH% value is then compared to the Alpha parameter. If there are such cryptocurrencies, which in a specific period of fMACDH% is more than Alpha, then in this period they will be purchased at the expense of the proceeds from the previous step. Moreover, the amount that will be used to purchase each of these cryptocurrencies will be determined in proportion to the difference between fMACDH% and Alpha. If such cryptocurrencies are not found, and in the previous step some cryptocurrencies were sold, then the amount received will be transferred to the purchase in the next period. At the output, we will have information about the value of the portfolio in each period. Alpha and Beta are entered into the model along with the input data. Alpha=Beta=0 was adopted for the initial testing of the algorithm. The block diagram of one iteration of this algorithm is shown in **Error! Reference source not found.**.

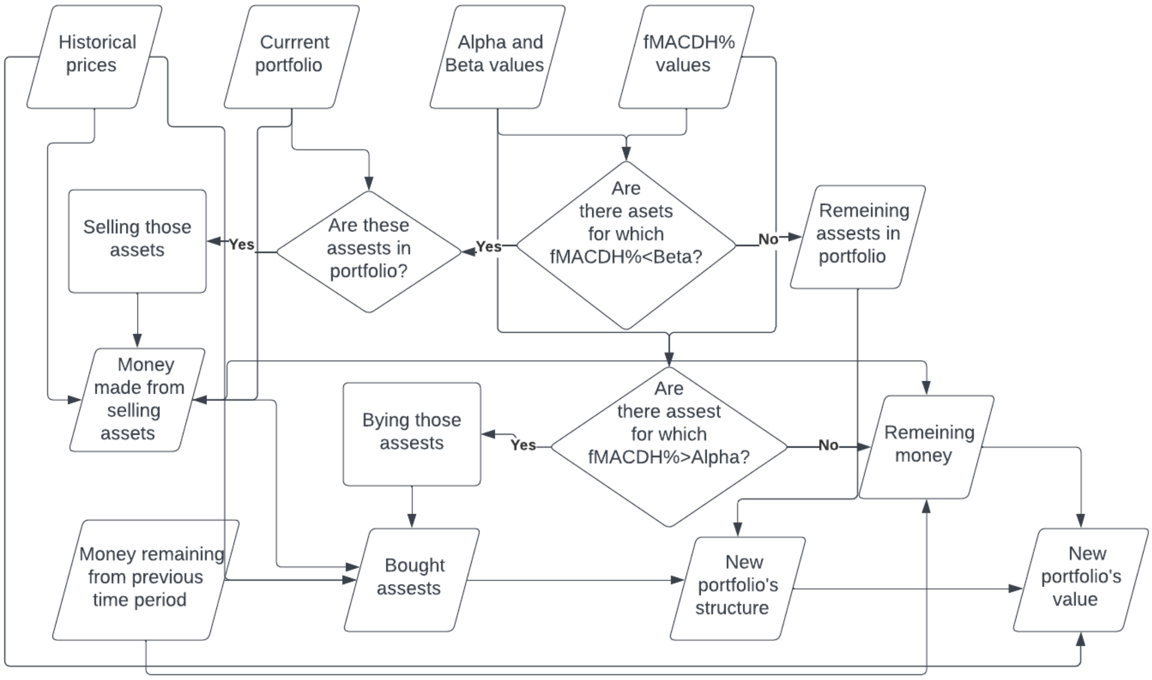

Figure 1: Block diagram of one iteration of the algorithm "Proportional dynamic rebalancing of the portfolio according to the Alpha-Beta fMACDH% criterion"

3. Results

The 10 cryptocurrencies with the largest market capitalization as of October 10, 2022, were selected for the study: Bitcoin, Ethereum, Tether, USD Coin, BNB, XRP, Binance USD, Cardano, Solana, and Dogecoin [12]. Prices were taken in the period from September 9, 2020, to October 9, 2022, that is, 761 observations. Based on the input data, several technical analysis indicators were calculated, namely: EMA with periods 12 and 26, MACD with signal line, MACDH, and MACDH%. To calculate the fMACDH% indicator, the Random Forest forecasting method was used with the number of constructed decision trees equal to 100. The model quality assessment for each cryptocurrency was carried out according to the R2 criterion (Table 1).

Table 1
R2 indicator of Random Forest

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.836	0.838	0.844	0.862	0.856	0.832	0.822	0.835	0.823	0.883

It was found that for each of the cryptocurrencies, the R2 indicator is greater than 0.8 in magnitude, which indicates the existence of a close connection in the models. Based on this, a conclusion was made about the feasibility of using Random Forest. Next, the number of previous periods that should be chosen to obtain the best results was determined. For this, 33 different regression Random Forest models were built, which took into account from 1 to 33 previous prices, respectively. To identify the dominant number of considered periods, the average value of R2 and its standard deviation were calculated. The graph of the relationship between the average value (horizontal axis) and the standard deviation R2 (vertical axis) is shown in **Error! Reference source not found.**. Since the standard deviation is smaller at 15 periods, it was decided to use this number. The values of R2 in this case are shown in Table 2.

When applying the algorithm "Proportional dynamic rebalancing of the portfolio according to the Alpha-Beta fMACDH% criterion", the question of the initial portfolio, which will be transferred to this algorithm, remained open. Since the first 40 days of the database will not be used in the algorithm due to the peculiarities of calculating fMACDH%, it was decided to build a Markowitz model on these data with the following restrictions: portfolio risk does not exceed 20%; none of the assets can be invested more than 25% of the total amount of the portfolio. The weights of the optimal initial portfolio are shown in Table 3. The block diagram of the modified algorithm is presented in **Error! Reference source not found.**.

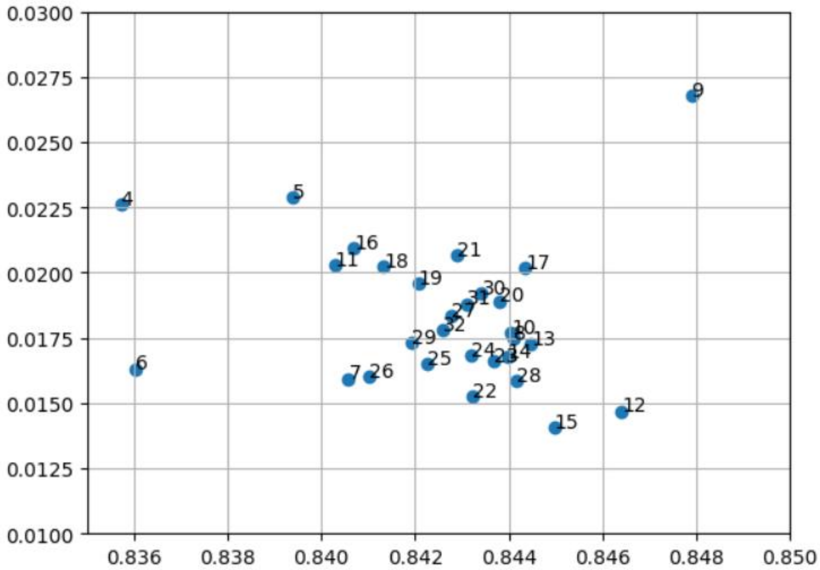

Figure 2: The ratio between the mean value and the standard deviation of R2

Table 2

R2 indicator of Random Forest taking into account 15 previous periods

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.841	0.837	0.847	0.854	0.860	0.829	0.838	0.835	0.820	0.879

Table 3

Weights of the Optimal Initial Portfolio

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.25	0.25	5.27e-8	5.08e-8	0.25	4.37e-7	5.10e-8	0.25	7.57e-8	2.35e-8

The next step is to evaluate the effectiveness of the model. An initial portfolio value of USD$10,000 was set. The change in the value of the portfolio during the operation of the algorithm is shown in **Error! Reference source not found.**, where the value of the portfolio is plotted on the vertical axis, and the observation number is plotted on the horizontal axis. Already at this stage of research, we can claim that this model is effective: with an initial cost of USD$10,000, the value of the portfolio at the end of the researched period reached about USD$100,000, that is, we received an ROI of 900%. Moreover, the peak cost during the entire period slightly exceeds USD$280,000. That is, as of the 380th day, the ROI was 2700%. The structure of the portfolio at the end of the period is presented in Table 4.

At peak values, the portfolio was also quite diversified, the number of assets in it varied from 2 to 6. The graph itself in **Error! Reference source not found.** looks quite interesting: it does not show a constant trend of growth or decline, but on the contrary, there are areas of slow growth, decline, and stability, as well as significant jumps and declines. The reason for this behavior needs further research in the future. After all, many factors could lead to this, a significant part of which can be exogenous, such as the market structure, changes in the policies of the governments of countries, and others. It is appropriate to investigate how exactly the value of the portfolio will change when we change the parameters Alpha, Beta, and w. First, let's see how it will behave if the Beta and w indicators are left constant, and the Alpha indicator is changed from 0 to 2.5. The corresponding graph is shown in **Error! Reference source not found.**, where areas of decline are indicated in darker blue, and areas of growth are indicated in lighter blue.

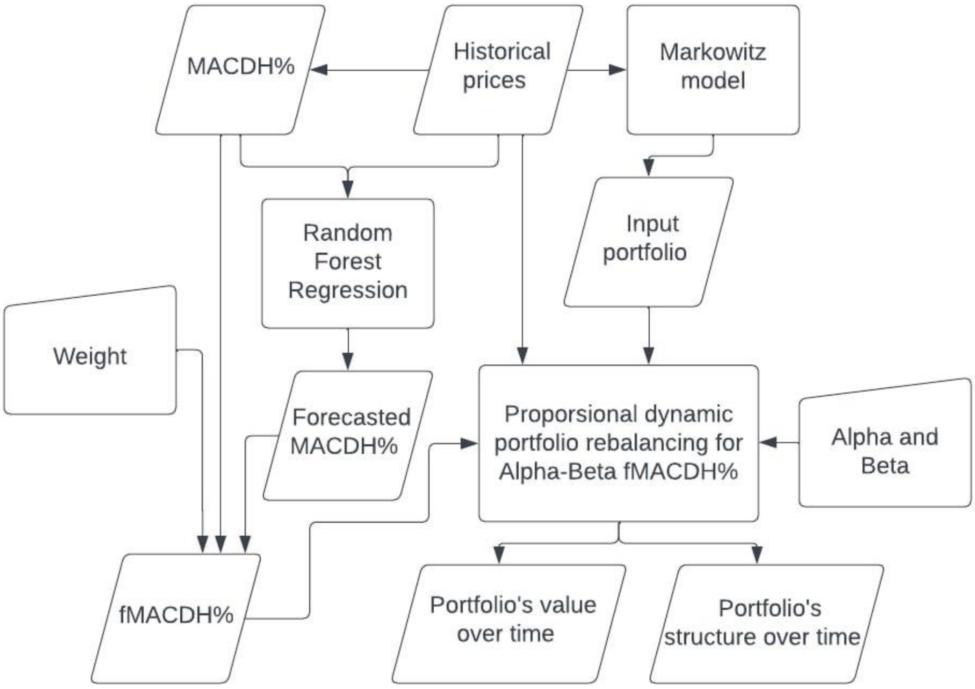

Figure 3: The block diagram of the modified algorithm

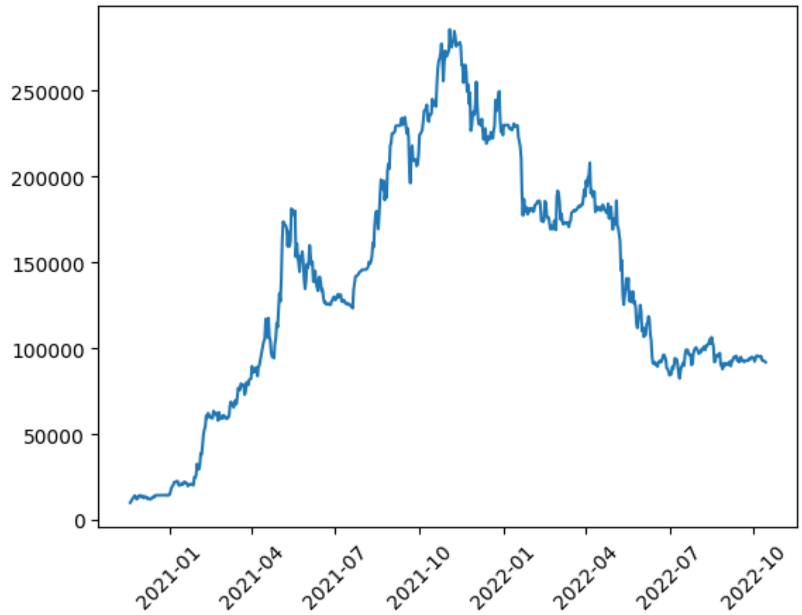

Figure 4: Change in portfolio value for a model with parameters Alpha=Beta=0, w=0.5

The results presented in **Error! Reference source not found.**, demonstrate that increasing the Alpha parameter gives better results in the long run. It was determined that when the value of Alpha increases, the areas of significant declines and falls become smoother, which leads to smaller values of local maxima and larger values of local minima. From this, it can be concluded that investors with a lower level of risk should use higher values of the Alpha parameter and vice versa. Now let's examine what will happen if we change the Beta indicator from -1 to 1, taking the Alpha indicators equal to 1.5 (since Alpha must be at least as much as Beta) and w=0.5 (**Error! Reference source not found.**). Now the situation is not so unambiguous. At the lowest Beta value studied, the value of the portfolio increased significantly at the beginning of trading but then showed worse results. Also, there is no clear upward or downward trend in the value of the portfolio as Beta increases – instead, it is wave-like, with each subsequent wave larger than the previous one. Based on the above conclusions, it was decided to build two more models, with values of Alpha=2, Beta=-0.5 and Alpha=1, Beta=0.5, and compare their results with the initial model and with each other.

Table 4

Portfolio structure during the last 5 days, the model with Alpha=0, Beta=0, w=0.5

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.01	0.36	0.05	0.43	0.01	0.0	0.04	0.10	0.00	0.00
0.00	0.36	0.05	0.43	0.01	0.0	0.04	0.10	0.00	0.00
0.00	0.00	0.09	0.45	0.00	0.0	0.17	0.00	0.29	0.00
0.00	0.00	0.09	0.45	0.00	0.0	0.17	0.00	0.28	0.00
0.00	0.00	0.09	0.46	0.00	0.0	0.17	0.00	0.28	0.00

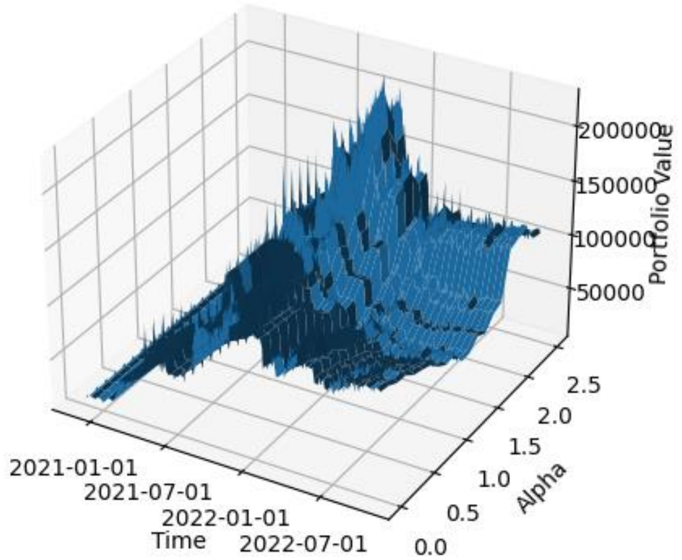

Figure 5: Change in the portfolio value depending on the Alpha parameter with Beta=0, w=0.5

The dynamics of the portfolio value at Alpha=2, Beta=-0.5 is shown in **Error! Reference source not found.**. The structures of both new portfolios at the end of the period are presented in Table 5 and Table 6. According to the results of applying the first model (**Error! Reference source not found.**), we have that the change in the value of the portfolio looks quite volatile with a clear peak in the middle of the period. When both parameters are zero, the algorithm can buy or sell assets at any time, resulting in higher transaction frequency and, as a result, higher portfolio volatility. In the second model, the change in portfolio value is less volatile compared to the first graph but still contains several distinct peak values. This model minimizes the number of transactions: it buys only assets with a significantly high expected return and sells only assets with a significantly low expected loss. **Error! Reference source not found.** shows a more aggressive rise in value with higher peaks, which may indicate that waiting for a stronger positive signal before buying can help capture larger market moves to the upside. Also unlike the first and third models, the peak value of the portfolio is significantly higher, and the value at the end of the period has not experienced such a significant drop compared to the peak value. The value of the portfolio in the third model shows moderate volatility with less pronounced peaks compared to the first model. Because of the high Beta value, the third model avoided not only loss-making assets but also assets with low expected returns. This may indicate that a conservative approach prevents large losses, but may also limit potential profits. Based on these observations, it can be assumed that higher values of Alpha and Beta can lead to lower volatility of the portfolio since the algorithm makes fewer transactions with stricter criteria for buying and selling. In addition, with zero Alpha and Beta values, the algorithm reacts to any small changes in fMACDH%, which can lead to frequent transactions and high portfolio volatility. From the results of Table 4, Table 5 and Table 6 it follows that an increase in the modulus of Alpha and Beta indicators leads to a decrease in the level of portfolio diversification. In the first portfolio, 3 assets were involved in the last 5 days, in the second, most of the value was in one asset, and the third - two or three assets. That is, portfolios derived from models with larger Alpha and Beta are more centralized and therefore riskier.

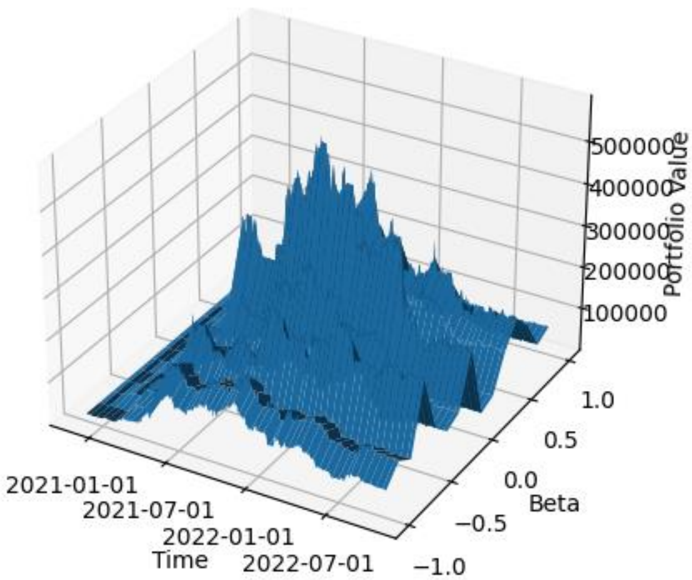

Figure 6: Change in the portfolio value depending on the Beta parameter with Alpha=1.5, w=0.5

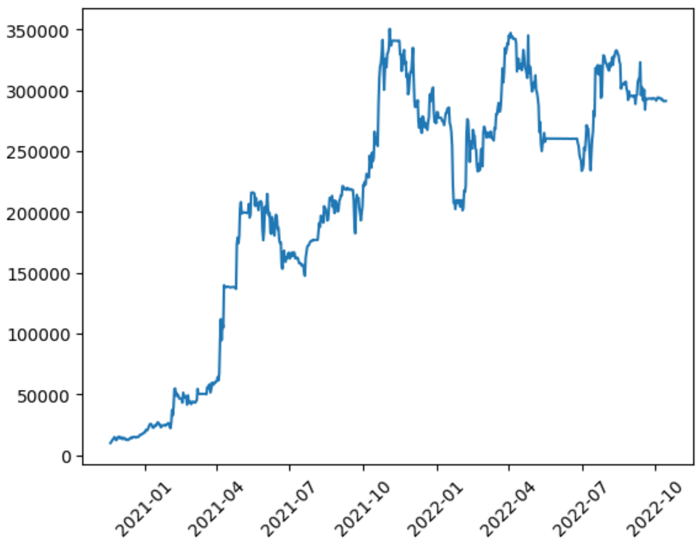

Figure 7: Change in portfolio value for a model with parameters Alpha=2, Beta=-0.5, w=0.5

Table 5

Portfolio structure during the last 5 days, the model with Alpha=2, Beta=-0.5, w=0.5

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.000	0.118	0.000	0.837	0.000	0.004	0.014	0.027	0.000	0.000
0.000	0.117	0.000	0.838	0.000	0.004	0.014	0.026	0.000	0.000
0.000	0.118	0.000	0.838	0.000	0.004	0.014	0.026	0.000	0.000
0.000	0.118	0.000	0.839	0.000	0.004	0.014	0.000	0.026	0.000
0.000	0.119	0.000	0.838	0.000	0.004	0.014	0.000	0.025	0.000

Therefore, the issue of the relationship between Alpha and Beta parameters and the choice of their nominal value is interesting and multifaceted and requires further investigation. The last parameter that remains to be investigated is w. Let's take Alpha=2.5 and Beta=0.7 and change w from 0 to 1. Note that with w=0 we will have a model that will be completely based on classic indicators of technical analysis.

Table 6

Portfolio structure during the last 5 days, the model with Alpha=1, Beta=0.5, w=0.5

Bitcoin	Ethereum	Tether	USD Coin	BNB	XRP	Binance USD	Cardano	Solana	Dogecoin
0.000	0.000	0.985	0.011	0.000	0.000	0.000	0.004	0.000	0.000
0.000	0.000	0.985	0.011	0.000	0.000	0.004	0.000	0.000	0.000
0.000	0.000	0.985	0.000	0.000	0.000	0.007	0.000	0.008	0.000
0.000	0.000	0.985	0.000	0.000	0.000	0.007	0.000	0.008	0.000
0.000	0.000	0.000	0.000	0.000	0.000	0.314	0.000	0.686	0.000

It was determined that adding a predicted component to the model made it possible to solve the problem of "sawtooth effects". Indeed, at w=0, changes in the portfolio occur very often, which leads to constant sharp changes in the structure of the portfolio and fluctuations in its value. Also, the effectiveness of the model has increased significantly since the introduction of the predicted component. At the same time, starting from the value of 0.2, no significant changes are observed.

4. Discussion

Cryptocurrencies represent significant investment interest, especially in the context of portfolio diversification. They are characterized by high volatility, which can lead to significant profits, but also high risks. The study showed that proportional dynamic portfolio rebalancing, based on the fMACDH% indicator and the Random Forest method, is an effective means of increasing the value of a cryptocurrency portfolio. It became especially important to establish that changing the parameters of Alpha and Beta has an impact on the volatility of the portfolio and its total value, where higher values of these parameters contribute to reducing volatility, although they can limit potential profits. It was also found that the parameter w plays a key role in determining the frequency and efficiency of trading operations. In addition, the study indicates the need for a balanced approach to the selection of model parameters, since an increase in the modulus of Alpha and Beta values can reduce the level of portfolio diversification, thereby increasing risks. In future research, it is proposed to try other prediction methods in determining the value of fMACDH%, to determine the optimal values of the parameters Alpha, Beta, and w, and to conduct a detailed study of the relationships between them. It is also worth considering the possibility of minimizing risk by establishing a condition that a certain percentage of the value of the portfolio should be in stablecoins and the other - in traditional cryptocurrency. Finally, the model can be improved beyond technical analysis by integrating data on macroeconomic indicators, the stock market, and Internet sentiment analysis.

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