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BITCOIN'S WEEKLY CLOSING PRICE FORECASTING MODEL

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ABSTRACT

The primary objective of this article is to provide a methodological approach to forecasting Bitcoin's weekly closing price, utilizing a correlation-indicator model. The study aimed to identify the parameters with the greatest impact on weekly bitcoin closing price forecasts, establish combinations of parameters that produce the most accurate forecasts, and determine how the final results and assigned points impact the success of the developed forecasting model. Three types of forecasts were considered: a weekly forecast of the Bitcoin closing price; a forecast of the Bitcoin price increase after the first price drop event; and a forecast of the Bitcoin price decrease after the first price increase event. The study is predicated on the weekly closing price of Bitcoin (with a sample size of 346 weeks between 2 April 2018 and 11 November 2024), the MACD indicator, and the Pearson correlation coefficients between the historical values of the studied indicators. The study involved building and testing a model to predict Bitcoin's weekly closing price. This model shows a higher probability than the actual historical results; the duration of unsuccessful forecasts is significantly lower than the number of opposite price movements according to historical data; in some tests, the model achieved 100% probability and zero failed forecasts. In general, the approach proposed by the authors enabled the identification of the parameters and sets of parameters with the greatest impact on the quality of Bitcoin price forecasting. The practical application of the proposed approach has demonstrated the efficacy of the correlation-indicator model in handling both known and unknown final data, thus facilitating its extensive application in forecasting the weekly closing price of Bitcoin in conditions of an unknown future.

Keywords: cryptocurrency, Bitcoin, Bitcoin price, forecasting, forecasting model, MACD, trader

JEL Classification: C53, C58, E47, G17

INTRODUCTION

It is evident that Bitcoin, in its capacity as the inaugural and most pervasive cryptocurrency, has garnered significant interest from researchers, investors, and financial analysts. The price of this asset is characterized by high volatility, which creates both unique profit opportunities and significant risks for investors. Moreover, the volatility of Bitcoin, attributable to the influence of various economic, regulatory, and technological factors, renders its value prediction challenging. Consequently, the accurate prediction of the Bitcoin price is a pressing task in the present day, as such forecasts have the potential to contribute to more efficient investment management, reduce financial losses, and increase the stability of the cryptocurrency market. Consequently, the development of an effective model for forecasting the weekly closing price of Bitcoin is becoming a necessary tool for investors, traders, and analysts. Although this is a rather complex and multifaceted task, the relevance of which is growing with the development of the cryptocurrency market, it is a project that must be given due consideration.

The relevance of this study is determined by the following aspects: the most accurate forecasting of Bitcoin value can improve risk management strategies and investment portfolios; the cryptocurrency market, unlike traditional financial markets, is less regulated, and therefore, price volatility requires improved approaches to modeling, analysis and forecasting; the development of machine learning and artificial intelligence methods opens up new opportunities for forecasting, which can help to increase the accuracy of predictions and reduce uncertainty.

Simultaneously, the complexity of anticipating the value of Bitcoin is attributable to the following factors: Bitcoin is not subject to traditional macroeconomic models, as its price is influenced by a variety of factors that extend beyond financial indicators. These include social perception, market expectations, and behavioral factors. The cryptocurrency market operates on a continuous basis, seven days a week, which generates a constant flow of new data and complicates the process of modeling and forecasting; the impact of exogenous events, such as changes in regulation, technological breakthroughs, or large Bitcoin transactions, can precipitate sudden price fluctuations, thereby rendering traditional forecasting methods ineffective. For instance, increased regulatory scrutiny can engender a reduction in investor confidence, while global differences in regulation can limit adoption and liquidity, and restrictions on mining can affect supply. In addition, the speculative nature of cryptocurrencies, in that most traders use them as a tool for speculation rather than as a means of exchange, can also have an impact.

It is evident that the demand for reliable forecasting models is driven by the complexity of Bitcoin price behavior. This is due to the fact that the cryptocurrency market is influenced by numerous factors, and existing financial instruments and analysis methods do not adequately reflect its specifics. This necessitates the development of new approaches and models that can account for the unique characteristics of digital assets. The study of this problem suggests that the methodological approaches used as the basis for analyzing and forecasting the price of Bitcoin, such as technical and fundamental analysis, market sentiment analysis, machine learning, and artificial intelligence, are very relevant and widely used today, but require further improvement.

LITERATURE REVIEW

The analysis and forecasting of Bitcoin prices have emerged as a highly complex and extensively researched domain within the realm of financial analytics in recent years. Due to its volatility, decentralized nature, and the influence of macroeconomic factors, Bitcoin has been the subject of numerous scientific studies that apply various forecasting methods, from classical econometric models to modern machine learning algorithms.

In the context of Bitcoin prices, contemporary analytical and forecast methodologies encompass a variety of approaches that are utilized extensively by analysts and traders:

1. Technical analysis based on historical data on prices and trading volumes and involving the use of classical econometric models and indicators such as moving averages, RSI, MACD, ARIMA, SARIMA, ARIMA-GARCH, etc. (Uras et al., 2020; Benzekri & Ozutler, 2021; De Leon et al., 2022; Haolin, 2023; Phung Duy et al., 2024; Ignatenko & Dokiienko, 2025 a, b, c).
2. Fundamental analysis that takes into account macroeconomic factors, market news, regulatory changes, and internal characteristics of Bitcoin, such as adoption rates and technological updates (Wang, 2024; Wahyuni et al., 2024; Peng et al.,2024).
3. The analysis of market sentiment, which employs data from social media, news outlets, and other sources to evaluate the prevailing sentiment among investors, has the capacity to influence the price of Bitcoin (Critien et al.,2022; Arslan, 2025; Htay et al.,2025).
4. Machine learning (ML) and artificial intelligence (AI) are both fields of study which involve the use of neural networks, deep learning models and forecasting algorithms to analyse large amounts of data, for example SVM, Random Forest, Naive Bayes, Logistic Regression (Pabuçcu et al., 2020; Basher & Sadorsky, 2022; Maleki et al., 2023; Cohen & Aiche, 2025).
5. Deep learning (DL) is the process of utilizing deep neural networks to discern intricate patterns within time series, and the following models are to be considered: LSTM, GRU, CNN, TCN, and hybrid models (Akbar et al., 2021; Guo et al., 2021; Jakubik et al., 2022; Ateeq et al., 2023; Kim et al., 2024; Omole & Enke, 2024; Kervanci et al., 2024; Cohen & Aiche, 2025).
6. The hybrid and specialised approaches constitute a combination of classical and modern methods, in addition to the incorporation of non-traditional data sources. For instance, Guo et al. (2021) incorporate blockchain transactions into their analyses, while Jakubik et al. (2022) incorporate financial news into their forecasts. Akbar et al. (2021) analyse social media sentiment, and Maleki et al. (2023) consider the impact of other cryptocurrencies on Bitcoin. Kleban &

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Stasiuk (2022) utilise machine learning methods based on FB Prophet time series and LSTM recurrent neural networks.

7. Economic and structural models that involve modelling fundamental economic processes: supply and demand, determinants, trends, etc. (Jalali & Heidari, 2020; Hartono & Suyanto, 2023; Rudd & Porter, 2025).

Consequently, in view of the substantial corpus of research on this issue and the heterogeneity of approaches adopted by contemporary authors, the enhancement of Bitcoin price forecasting methods is a pivotal and imperative undertaking for the advancement of the theory and practice of cryptocurrency trading. The enhancement in the precision of forecasts is a notable benefit, as is the contribution to a more profound comprehension of market dynamics, a crucial aspect for investors, analysts, and regulators.

The authors' previous research focused on analyzing the relationship between the dynamics of the minimum/maximum price of bitcoin on the weekly timeframe and the MACD histogram (Ignatenko & Dokiienko, 2025 b,c), as well as the analysis of the relationship between the dynamics of the closing price of bitcoin and the MACD histogram to formulate traders' forecasts within the framework of technical investment analysis (Ignatenko & Dokiienko, 2025a). These analyses were partial in nature, as they took into account a limited range of factors. In this study, the authors propose a comprehensive alternative approach to forecasting the weekly closing price of Bitcoin. This approach is distinct from existing ones in that it considers fifteen parameters that have the greatest impact on the forecast. It also determines the combination of parameters that gives the most accurate forecast and establishes the impact of the final results and the number of points given to them on the success of the forecast. The authors propose the implementation of a correlation-indicator model, in which the forecast of Bitcoin price is formed on the basis of an assessment of the relationship between the price of Bitcoin, the MACD indicator, and Pearson correlation coefficients between the historical values of these indicators.

AIMS AND OBJECTIVES

The main purpose of the present study was to devise a correlation-indicator forecasting model that utilizes established bitcoin price data to facilitate more precise weekly closing price predictions than the mean actual results.

The primary tasks that were identified are outlined below: firstly, to ascertain the parameters that exert the most significant influence on the formation of the forecast; secondly, to determine the combinations of parameters that yield the most precise forecast; and thirdly, to establish the impact of the final results and the number of points allocated to them on the success of the forecast.

The study considers three types of forecasts: firstly, a weekly forecast of the closing price of Bitcoin; secondly, a forecast of price growth following the initial price drop; thirdly, a forecast of price decline after the first instance of Bitcoin price growth.

METHODS

Parameters of the forecasting model

The authors have developed a correlation-indicator model to forecast the weekly closing price of Bitcoin. The model is a deterministic empirical system in which the Bitcoin price forecast is formed based on the evaluation of the relationship between the values of Bitcoin price, the MACD indicator, and the Pearson correlation coefficients between the historical values of these indicators.

The model conducts scoring using the formula:

$$F=\sum P_n \tag{1}$$

where F – Forecast (sum of all points); P – parameters (numerical value of parameters); n – parameter number.

The model incorporates a total of 15 parameters, each of which can assume one of three possible values: a positive value, denoting a growth forecast; a negative value, denoting a decline forecast; or a value of zero, denoting a neutral forecast or an absence of data.

Parameter 1 (P_1) – excess of the number of weeks with an increase in the closing price over the number of weeks with a decrease in the closing price:

$$P_1 = Pr_1 - Pr_2 \quad (2)$$

where Pr_1 – number of weeks of closing price growth, %; Pr_2 – number of weeks of closing price decline, %.

Parameter 2 (P_2) – the prevailing tendency exhibited by the mean series of uninterrupted closing price movements in a single direction over the present series of closing price movements:

$$P_2 = Pr_{avg} - Pr_{cur} \quad (3)$$

where Pr_{avg} – average series of continuous closing price movement in one direction, weeks; Prcur – current series of continuous closing price movement in one direction, weeks.

Parameter 3 (P_3) – the excess of the maximum series of continuous closing price movement in one direction over the current series of price movement

$$P_3 = Pr_{max} - Pr_{cur} \quad (4)$$

where Pr_{max} – maximum series of continuous closing price movement in one direction, weeks; Pr_{cur}. – current series of continuous closing price movement in one direction, weeks.

Parameter 4 (P_4) – outweighing of the series of continuous closing price movements that ended this week over the continued series:

$$P_4 = 100 - Pr_{fin} \quad (5)$$

where Prf_{in} – the number of series of continuous closing price movements in one direction that ended in the current week, %.

Parameter 5 (P_5) – number of weeks with MACD histogram growth over weeks with MACD histogram fall:

$$P_5 = M_1 - M_2 \quad (6)$$

where M_1 – number of growth weeks of MACD, %; M_2 – number of weeks of MACD decline, %.

Parameter 6 (P_6) – the average MACD histogram series outweighs the current one:

$$P_6 = M_{avg} - M_{cur} \quad (7)$$

where M_{avg} – average series of continuous movement of the MACD histogram in one direction, weeks; M_{cur} – current series of continuous MACD movement in one direction, weeks.

Parameter 7 (P_7) – overweighing of the maximum series of the MACD histogram over the current one:

$$P_7 = M_{max} - M_{cur} \quad (8)$$

where M_{max} – maximum series of continuous MACD histogram movement in one direction, weeks; M_{cur} – current series of continuous MACD movement in one direction, weeks.

Parameter 8 (P_8) – the series of uninterrupted MACD histogram movements that concluded this week prevailed over the ongoing series:

$$P_8 = 100 - M_{fin} \quad (9)$$

where Mf_{in} – number of series of continuous MACD histogram movement in one direction that ended during the current week, %

Parameter 9 (P_9) – repetition of the MACD histogram movement of the previous week by the closing price of the current week. The zone of the beginning of the current MACD histogram movement is taken into account, with the calculation being performed separately for the series of growth and decline of the MACD histogram.

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Parameter 10 (P_{10}) – Pearson's correlation coefficient between the change in the previous week's opening price and the change in the current week's MACD histogram:

$$P_{10}=\frac{\Sigma(OPr_{i-1}-\overline{OPr})(M_i-\bar{M})}{\sqrt{\Sigma(OPr_{i-1}-\overline{OPr})^2\Sigma(M_i-\bar{M})^2}} \quad (10)$$

where OP_{ri-1} –separate value of opening price change shifted 1 week earlier in relation to MACD change value; $\overline{OPr}$ – average value of opening price change; M_i – individual value of MACD histogram change; $\bar{M}$ – average value of MACD histogram change.

Parameter 11 (P_{11}) – Pearson's correlation coefficient between the change in the maximum price in the previous week and the change in the MACD histogram in the current week:

$$P_{11}=\frac{\Sigma(HPr_{i-1}-\overline{HPr})(M_i-\bar{M})}{\sqrt{\Sigma(HPr_{i-1}-\overline{HPr})^2\Sigma(M_i-\bar{M})^2}} \quad (11)$$

where HP_{ri-1} – separate value of the maximum price change shifted 1 week earlier in relation to the MACD change value; $\overline{HPr}$ – average value of the change in the maximum price.

Parameter 12 (P_{12}) – Pearson's correlation coefficient between the change in the previous week's minimum price and the change in the current week's MACD histogram:

$$P_{12}=\frac{\sum(\mathrm{LPr_{i-1}}-\overline{\mathrm{LPr}})(\mathrm{M_i}-\bar{\mathrm{M}})}{\sqrt{\sum(\mathrm{LPr_{i-1}}-\overline{\mathrm{LPr}})^2\sum(\mathrm{M_i}-\bar{\mathrm{M}})^2}} \quad (12)$$

where LP_{ri-1} – separate value of the minimum price change shifted 1 week earlier in relation to the MACD change value; $\overline{LPr}$ – average value of change in the minimum price.

Parameter 13 (P_{13}) – Pearson's correlation coefficient between the change in the previous week's closing price and the change in the current week's MACD histogram:

$$P_{13}=\frac{\Sigma(Pr_{i-1}-\bar{Pr})(M_i-\bar{M})}{\sqrt{\Sigma(Pr_{i-1}-\bar{Pr})^2\Sigma(M_i-\bar{M})^2}} \quad (13)$$

where P_{ri-1} – a separate value of the closing price change shifted 1 week earlier in relation to the MACD change value; $\overline{Pr}$ – average price change.

Parameter 14 (P_{14}) – Pearson's correlation coefficient between the change in the maximum price in the current week and the change in the MACD histogram in the previous week:

$$P_{14}=\frac{\Sigma(HPr_i-\overline{HPr})(M_{i-1}-\bar{M})}{\sqrt{\Sigma(HPr_i-\overline{HPr})^2\Sigma(M_{i-1}-\bar{M})^2}} \quad (14)$$

where HPr_i – separate value of the change in the maximum price; $\overline{HPr}$ – average value of change in the maximum price; M_{i-1} – separate value of MACD histogram change, shifted 1 week earlier in relation to the value of maximum price change.

Parameter 15 (P_{15}) – Pearson's correlation coefficient between the change in the minimum price in the current week and the change in the MACD histogram in the previous week:

$$P_{15}=\frac{\Sigma(LPr_i-\overline{LPr})(M_{i-1}-\bar{M})}{\sqrt{\Sigma(LPr_i-\overline{LPr})^2\Sigma(M_{i-1}-\bar{M})^2}} \quad (15)$$

where LPr_i – individual value of change in the minimum price; $\overline{LPr}$ – average value of change in the minimum price.

The calculations were based on the following indicators:

1. Exponential moving averages (EMA):

$$EMA_{week}=(Price_{week}\times Multiplier)+(Price_{last\_week}\times(1\text{-}Multiplier)) \quad (16)$$

$$\text{Multiplier} = \frac{2}{N+1} \tag{17}$$

where $Price_{week}$ – current closing price; EMA_{last_week} – EMA value for the previous week; Multiplier – multiplier; N – period EMA

2. Moving Average Convergence Divergence (MACD)

$$MACD = EMA_{12} - EMA_{26} \tag{18}$$

where EMA_{12} – 12-period exponential moving average (for a short period); EMA_{26} – 26-period exponential moving average (for a long period)

3. The signal line (9-period EMA from MACD) is an exponential moving average (EMA) calculated on the basis of MACD values for the last 9 periods and is used to smooth out MACD values, as well as to identify points of intersection with the main line for buy/sell signals.

$$\text{Signal Line} = EMA_9(MACD) \tag{19}$$

where MACD – MACD values obtained from the difference between EMAs with periods of 12 and 26.

4. MACD Histogram, which shows the difference between the MACD and the signal line and helps to visualize how much the MACD deviates from its signal line.

$$\text{Histogram} = MACD - \text{Signal Line} \tag{20}$$

where MACD – MACD values obtained from the difference between EMAs with periods of 12 and 26; Signal Line – 9-period EMA from MACD.

The model starts calculations from the week starting 9.04.2018 and calculates the total score for each subsequent week until 11.11.2024. The model assigns scores depending on the type of test (Table 1).

Table 1. An algorithm for assigning points in each iteration of calculations.

Parameters	Assessment algorithm
P1	If Pr1 > Pr2, then a point for growth; if less, a point for fall; if equal, no point is given
P2; P3	If Pravg > Prcur, Prmax > Prcur, then the score is in the same direction as the closing price movement. If equal, no score is given. Variables are counted separately for the series of rise and fall of the closing price
P4; P8	If in the following week the movement in the same direction continued for more than 50% of the previous cases, a score in the same direction of the closing price movement is assigned. If less than 50%, a point in the opposite direction is assigned. If equal to 50%, no score is assigned
P5	If M1 > M2, then the score is for an increase in the closing price. If it is less, then the point for falling. If equal, no point is given
P6; P7	If Mavg > Mcur, Mmax > Mcur, then the score in the same direction of the closing price movement. Variables are counted separately for MACD histogram rise and fall series.
P9	If in the following week, on previous occasions of observation, the closing price repeated the direction of the MACD histogram movement, then a score is given for the closing price in the same direction of the MACD histogram movement in which it moved in the previous week
P10 – P15	If P10 >= 0.1, P11 >= 0.1, P12 >= 0.1, P13 >= 0.1, P14 >= 0.1, P15 >= 0.1 for the current iteration of calculations, then a score is given in the direction of price movement in the previous week. If P10 < 0.1, P11 < 0.1, P12 < 0.1, P13 < 0.1, P14 < 0.1, P15 < 0.1, there is no point

The resulting cumulative score in each iteration of the calculation is the price forecast for the following week:

1. If the total score is greater than zero (F>0), then for the next week, the weekly closing price is expected to grow relative to the previous week.
2. If the total score is less than zero (F<0), then for the next week, the weekly closing price is expected to fall in relation to the previous week.
3. If the total score is equal to zero (F=0), there is no prediction.

The model then compares the predicted result with that of the following week:

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1. The forecast is fulfilled if the forecast is greater than zero and there was an increase the following week, or if the forecast is less than zero and there was a decrease the following week.
2. Unfulfilled prediction: if the forecast is greater than zero and there was a decline in the next week; if the forecast is less than zero and there was an increase in the next week; or if there was no forecast, the unfulfilled prediction is made regardless of whether the closing price rose or fell in the next week.

Testing the forecasting model

The model assigns scores depending on the type of test: testing each parameter separately with unknown/known outcomes over the entire study period. (Appendix 1); testing combinations of parameters with unknown/known outcomes over the entire study period. (Appendix 2); random testing of combinations of parameters with unknown endpoints over the entire study period.

The difference between 'unknown' and 'known' final data over the entire study period is that in the former case, the model for each iteration of the calculations uses new data about the:

- excesses in the number of weeks with an increase in the closing price or MACD histogram compared to the number of weeks with a decrease in the closing price or MACD histogram (parameters P1 and P5);
- average and maximum series of rise and fall of the closing price and MACD histogram (parameters P2, P3, P6, P7);
- excesses of the series of continuous movement in one direction of the closing price or MACD that ended this week over the continuous ones (parameters P4 and P8);
- the closing price of the current week repeats the movement of the MACD histogram of the previous week (parameter P9);
- all correlations (parameters P10 – P15).

In the second case, the model is aware of the final data, which is obtained during the final iteration and used for calculations during each subsequent iteration. However, in both cases, the model is unaware of when a particular series of closing prices or MACD movements will end. In other words, the model cannot predict whether a particular series will last three weeks or fifteen weeks.

Value 1 – the model assigned a constant 1 point to this parameter. Value 'V' – the model assigned a Variable score to this parameter, which is calculated as follows:

1. P9: If, in the previous week, the closing price repeated the direction of the MACD histogram movement, then a score equal to n/100 is given for the closing price moving in the same direction as the MACD histogram movement. Where n is the percentage of times that the price repeats the same MACD movement in the current iteration of calculations (or in the final iteration of the corresponding test group). The variable n is calculated by analogy with the study of Ignatenko & Dokiienko (2025a).
2. P10: if P10 >= 0.1 for the current iteration of calculations (or for the final iteration in the corresponding test group), then a score equal to P10 in the direction of price movement in the previous week is given; if P10 < 0.1, then nothing is put.
3. P11 – P15: if P11 – P15 >= 0.1 for the current calculation iteration (or for the final iteration in the corresponding test group), then a score equal to P11 in the direction of price movement in the previous week is given; if P11 – P15 < 0.1, then nothing is placed.

In turn, randomly testing combinations of parameters with unknown endpoints over the entire study period involves assigning a score to a rise or fall in random order.

Thus, a total of 134 tests were conducted: 22 tests each for 1 parameter (with known and unknown endpoints), 30 tests each for combinations of parameters (with known and unknown endpoints), and 30 tests with random assignment of scores (with unknown endpoints).

Algorithm for assessing the model performance

The model's results were compared with known historical data. The probability of events occurring and the length of a series of opposite events were compared. The key points chosen were 0%, 5%, 6.52% and 10%. The 5% and 10% points were chosen at random, whereas 6.52% represents the average deviation of the subsequent closing price from the previous one during the period from 2 April 2018 to 11 November 2024 — a total of 346 weeks. For the probabilities, the comparison was made on the basis that, if the closing price repeated the direction of the MACD histogram movement in the previous week, a score equal to n/100 was given for the closing price moving in the same direction as the MACD histogram movement in the previous week. Here, n represents the percentage of times that the price repeats the same MACD movement in the current iteration of calculations (or in the final iteration of the corresponding test group). The variable n is calculated by analogy with the study of:

- 0% – historical movement of the next closing price above the previous closing price was compared to the success of the forecast direction calculated by the model; 0% - historical movement of the next closing price below the previous closing price was compared to the failure of the forecast direction calculated by the model;
- historical movement of the next closing price above -5%, -6.52%, -10% or below 5%, 6.52%, 10% of the previous closing price was compared to similar levels of the forecasted direction; historical movement of the next closing price below -5%, -6.52%, -10% or above 5%, 6.52%, 10% of the previous closing price was compared to similar levels of the forecasted direction.

The results obtained in the tests were further refined by grading the number of points assigned by the model in each test. The scores are as follows: 0, 1, 2, 3, 4, 5, 6, 7, 7.3.

RESULTS

The results of the study are categorized by forecast type into three categories. These categories provide an evaluation of the most effective parameters and combinations, as well as the impact of forecast scores, in line with the study's original objectives.

Weekly forecasts

The results of the weekly tests show an improvement in probabilities (Figure 1) for all levels: 0%, 5%, 6.52% and 10%. In turn, the lengths of the opposite series show a decrease from 1 to 4 events compared to historical data (Figure 2).

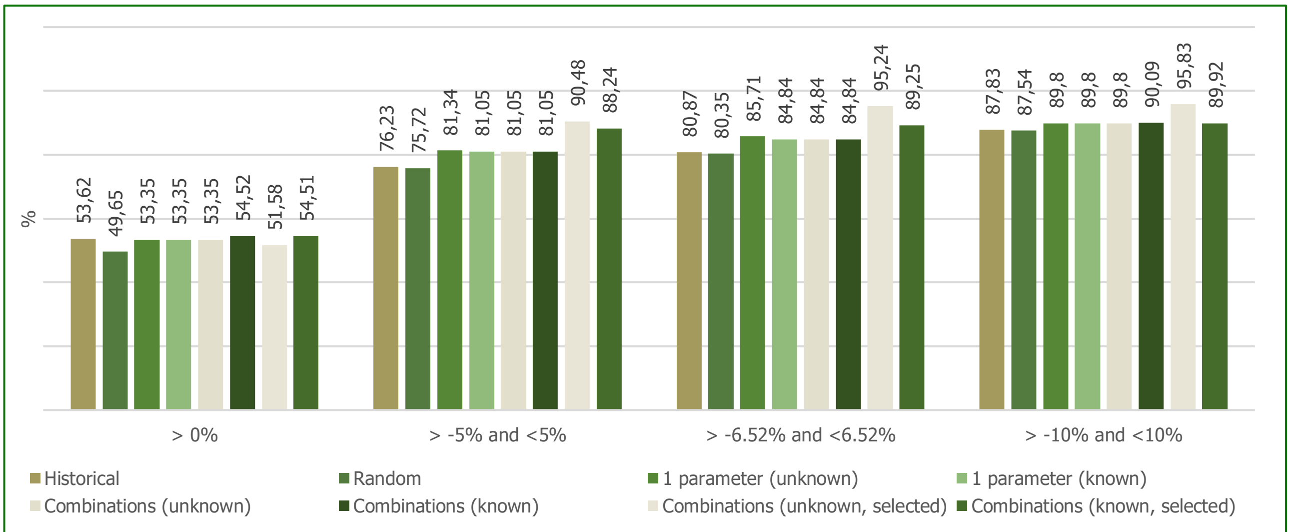

Figure 1. Probability comparison (weekly).

Explanation of abbreviations: unknown: unknown final data; known: known final data; random: tests with random assignment of scores; historical: actual historical data; selected: tests selected by the following criteria: maximum correlation between scores and probability.

We subtracted 0.1 points from the maximum correlation for each price level to provide a broader view of the tests rather than focusing on individual results. Thus, the range was from 0.31 to 1 across different price levels. The number of events for scores of 0 and 1 must be greater than 20.

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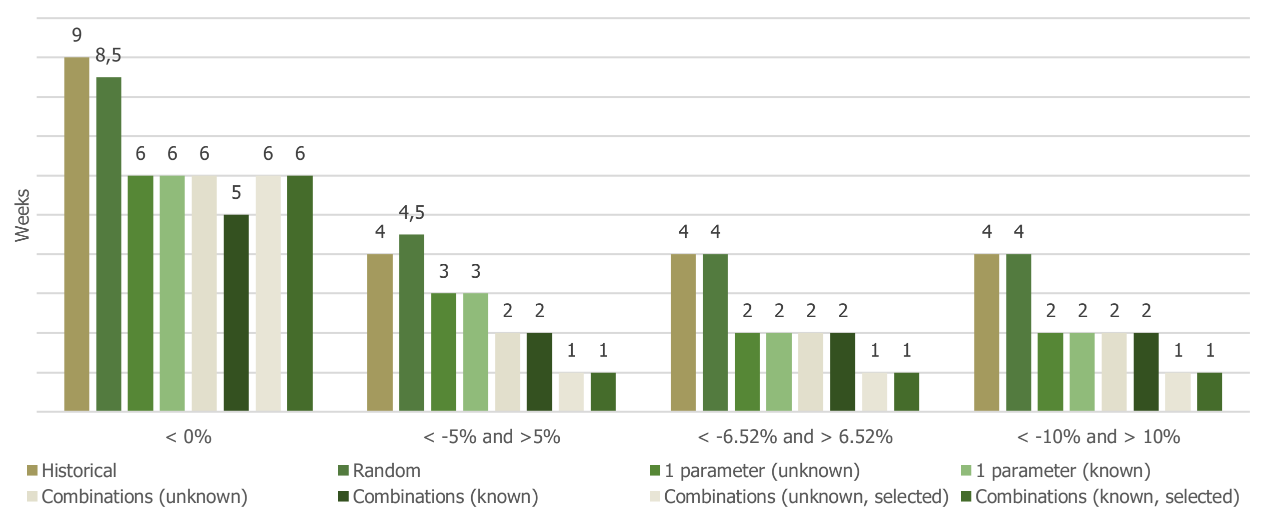

Figure 2. Comparison of lengths of opposite series (weekly).

For tests of parameter 1 in this type of forecasts (weekly), no selection by criteria was performed, as the model did not assign more than 1 point in tests of parameter 1, and, therefore, it shows the same forecasts as in tests of parameter 1, i.e., for each week — 344.

Table 2 shows the most effective tests for each level. These are categorized by probability and the length of the opposing series. Randomized tests are not presented because the data are averages of all 30 tests rather than maximum values. Random testing was conducted to determine the reference line. The aim was to establish whether directional prediction produces random results or whether they are still valid. It transpired that the null level (0%) in the random tests conformed to the 50/50 rule (the result was 49.65%), i.e., it was random. While this is slightly lower than the actual historical closing price movement (53.62%), the other levels in the random tests were very close to the actual values (Figure 1). The same trend is evident in the lengths of the opposite series (Figure 2).

Table 2. Best tests by weekly results.

Test type	0%		5%		6.52%		10%	
	%	length	%	length	%	length	%	length
1 parameter (unknown)	5	15,16	1	1,5,10,14	1	1,5	1	1,5
1 parameter (known)	1,5	3,15-18	1,5	1-3,5,7, 9-14,17-22	1, 5	1,5	1,5	1-5,15-18
Combinations (unknown)	23,25, 29, 30	2,3,10, 15,20,23	24-30	2,3	24-30	2,3,11,13, 20,24-30	13	2,3,11-13, 15,20,23-30
Combinations (known)	23	10,23	14,24-30	14	24-30	1-4,7,11, 12,14,15, 20, 23-30	6	1-4,6,7,11, 12,14,15,17 , 20,21,23-30
Combinations (unknown, max correlation)	3	3	6,12,18,22	6,12,18,22	5,6,21	5,6,21	4,12	4,12
Combinations (known, max correlation)	5,21	5,21	5,6,10-12, 15,20,21	5,6,10-12, 15,20,21	5,6,10 12,21	5,6,10, 12,21	10	10

There are no big differences between the results for 1 parameter and combinations of parameters (Figure 1), but the criterion-selected tests show a stronger improvement in the probabilities, although they lead to a decrease in the average number of predictions from 344 to 211, which is explained by the increase in the number of scores, because not every prediction received many scores.

The best results in terms of opposite series lengths (Figure 2) for the 5%, 6.52% and 10% levels are for the criterion – selected tests — length of only 1 event, which is 4 times shorter than the historical series. However, for the zero level, the criterion-selected tests showed an average length of 6 series. The shortest length here was for tests with combinations with known final data — 5 events, which is 1.8 times less than the historical series of 9 events.

Forecasts for growth after the first fall

This section evaluates tests that fulfill the following conditions: the previous week should be the first price drop; the model should make a forecast for growth. Fall forecasts and long fall series were excluded, i.e., the price fall event must be the first in the series. The results were compared with the historical occurrence of a closing price rise event after the first closing price fall event.

The results of the tests for closing price growth after the first downside event show a significant improvement in both the probabilities (Figure 3) and the lengths of the opposite series (Figure 4), which decreased by a factor of 1.7-5 (compared to historical data), and at the 10% level disappeared altogether, i.e., every prediction was correct.

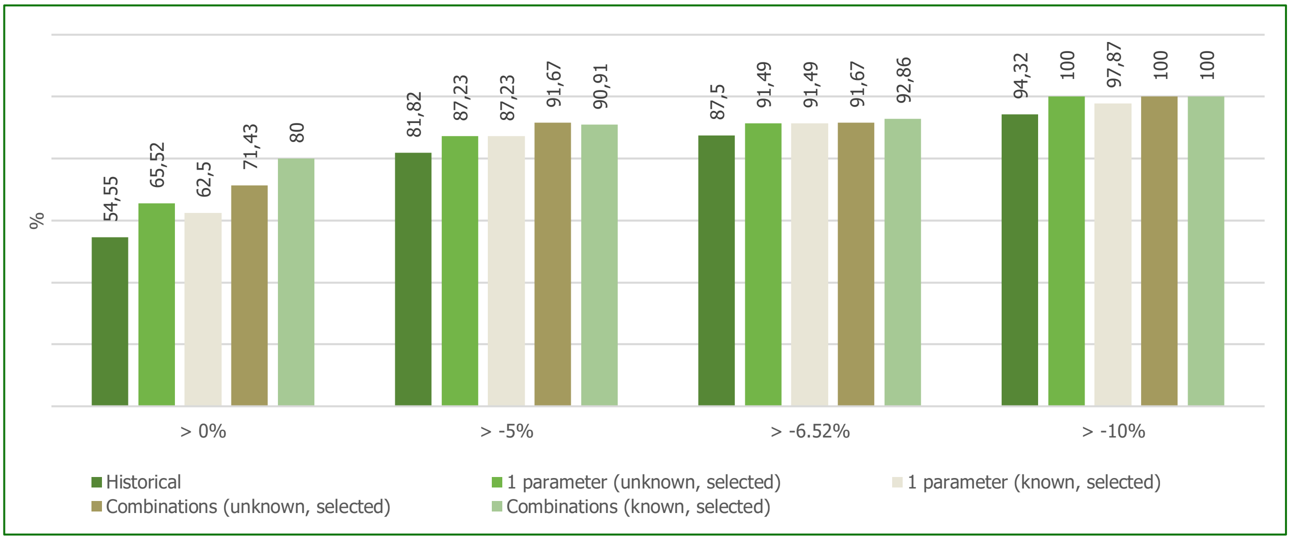

Figure 3. Comparison of probabilities for price growth after the first fall.

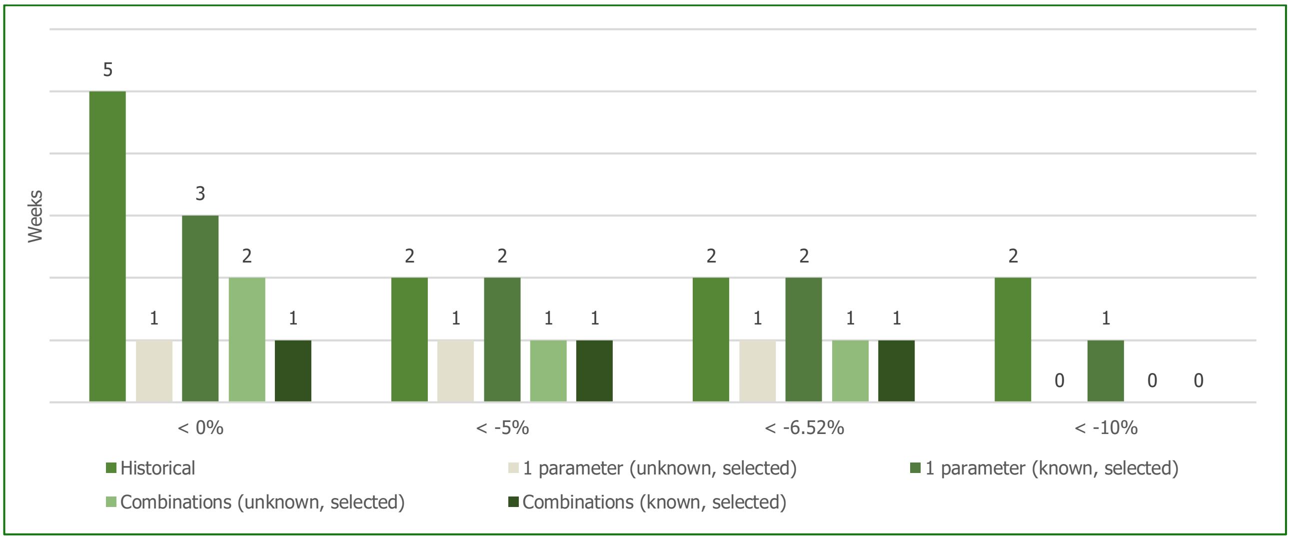

Figure 4. Comparison of lengths of opposite series (price drop after the first drop).

Selection criteria in this type of forecast:

- for combinations of parameters: the maximum correlation between scores and probability (minus 0.1 point from the correlation) — it was between 0.63 and 1 for different price levels; the number of events for scores 0 and 1 must be greater than 20;
- for the single-parameter tests, correlation was not considered because the model did not assign more than 1 score in the tests, i.e., there is not a long enough series of numbers to determine correlation; the number of events for scores of 0 and 1 must be greater than 20.

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Table 3 presents the best tests for each level. They are not separated here by probabilities and lengths, as they are the same tests selected according to the criteria described above.

Table 3. Best tests for price growth after the first fall.

Test type	0%	5%	6.52%	10%
1 parameter (unknown, quantity > 20)	1,4-16,19-22	1,4-16,19-22	1,4-16,19-22	1,4-16,19-22
1 parameter (known, quantity > 20)	1,4-8,10-16, 19-22	1,4-8,10-16, 19-22	1,4-8,10-16, 19-22	1,4-8,10-16, 19-22
Combinations (unknown, max correlation)	1-3,6,8,14,19	11,19,28,30	19,21	22,24,26-29
Combinations (known, max correlation)	1,4,7,13,14,19, 20,24-27, 9	11,12,15	11,15,21	4,7,8,11,18, 21-29

There are no significant differences between predictions with known and unknown endpoints for parameter combinations. However, tests with one parameter and unknown endpoints perform two to three times better than tests with one parameter and known endpoints, even if it is not the same parameter. The score division also leads to fewer predictions: if there were historically only 88 events that satisfied the input conditions, the model would make an average of 54 predictions for one parameter and 30 for parameter combinations.

Predictions for a fall after the first rise

This section evaluates tests that fulfil the following conditions: the previous week must represent the first instance of price growth, and the model must forecast a fall. Growth forecasts and long growth series were not considered; in other words, the price growth event must be the first in the series. The results show significant improvements in the probabilities (Figure 5) and lengths (Figure 6) of the opposite series compared to historical occurrences of closing price declines after the first closing price growth.

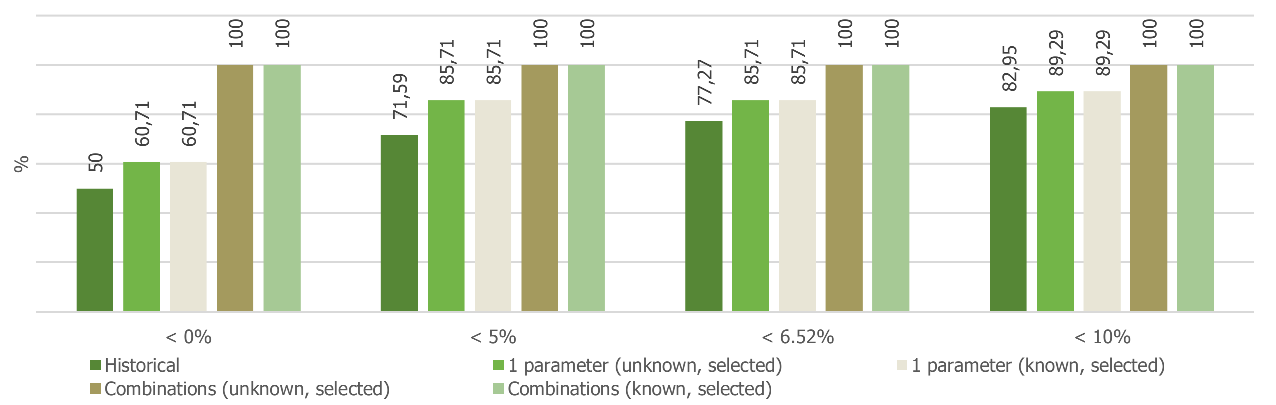

Figure 5. Comparison of probabilities for the price fall after the first growth.

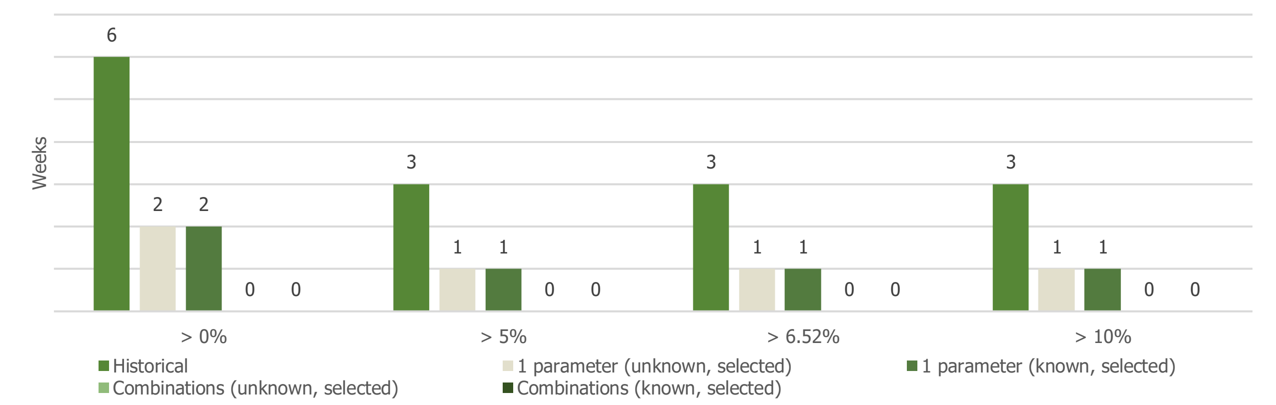

Figure 6. Comparison of lengths of opposite series (price growth after the first growth.

Selection criteria in this type of forecast:

- for combinations of parameters: maximum correlation between scores and probability (minus 0.1 point from correlation) - it ranged from 0.77 to 1 for different price levels. The number of events for scores 0 and 1 should be greater than 2 (a small number due to the very small number of events satisfying the input conditions - on average, only 6);
- for single-parameter tests: correlation was not taken into account because the model did not assign more than 1 point in the tests, i.e., there is not a long enough series of numbers to determine correlation. The number of events for scores 0 and 1 must be greater than 20.

Table 4 presents the best tests for each level. They are not separated here by probabilities and lengths, as they are the same tests selected according to the criteria described above.

Table 4. Best tests for price drop after the first rise.

Test type	0%	5%	6.52%	10%
1 parameter (unknown, quantity > 20)	4, 6-16, 19-22	4, 6-16, 19-22	4, 6-16, 19-22	4, 6-16, 19-22
1 parameter (known, quantity > 20)	6-8, 10-16, 19-22	6-8, 10-16, 19-22	6-8, 10-16, 19-22	6-8, 10-16, 19-22
Combinations (unknown, max correlation)	18, 19	12, 18, 19	12, 18, 19	18, 19
Combinations (known, max correlation)	5, 13, 18, 19	5, 13	5, 13	5, 13

The results of the tests for the closing price drop after the first growth event show a significant improvement in the probabilities for the one-parameter tests, with improvements of up to 100% for the parameter combination tests at all levels (see Figure 5). This leads to a decrease in the lengths of the opposite series in the parameter combination tests to zero and a decrease in the lengths of the opposite series in the one-parameter tests by a factor of three compared to the actual historical values (Figure 6).

In this type of prediction, the results of tests with known and unknown endpoints are the same. However, if there were historically 89 events that satisfied the input conditions, the model made a prediction in an average of 39 cases in tests with one parameter, and an average of six cases in tests with combinations of parameters.

DISCUSSION

Previous studies by Ignatenko and Dokiienko (2025a, b, c) suggest that the probability of a trend change increases as a series of price movements in one direction grows. However, despite the general prevalence of rises over falls, there were frequent instances of strong price changes (5–10% or more) in opposite directions in two neighboring weeks during the observation period from 2018-04-02 to 2024-11-11. For instance, a price drop of less than 5% was followed by an increase of more than 5% only 34 times; a drop of less than 6.52% was followed by an increase of more than 6.52% only 22 times; a drop of less than 10% was followed by an increase of more than 10% only five times; and a change from an increase to a decrease or vice versa (regardless of size) occurred 176 times.

During the study period, there were also instances of double price changes, where the price fluctuated between two extremes twice in succession, i.e., the trend resumed after a sharp reversal. These occurred 6 times for a 5% change, 3 times for a 6.52% change, 1 time for a 10% change, and 92 times for a change in direction regardless of the boundary. In practice, such 'turbulence' leads to the triggering of stop-losses, resulting in a trader losing money even if they predicted the general direction of price movement correctly.

This model for predicting the weekly closing price of Bitcoin was developed to increase the probability of determining the movement of the closing price. The model was tested in 134 different variations. These included one-parameter tests, combination tests, and tests with random assignment of scores:

1. The results of the weekly tests show a slight improvement in probabilities for all levels: 0%, 5%, 6.52% and 10%. In turn, the lengths of the opposite series show a decrease from 1 to 4 events compared to historical data.
2. The results of the tests for closing price growth after the first downside event show a significant improvement in both the probabilities and lengths of the opposite series, which decreased by a factor of 1.7-5 (compared to historical data), and at the 10% level disappeared altogether.

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3. The results of tests for the closing price drop after the first growth event show a significant improvement of probabilities in the tests of 1 parameter and an improvement of up to 100% in the tests of parameter combinations for all levels. In turn, this leads to a decrease in the lengths of opposite series in the tests of parameter combinations to zero, and a decrease in the lengths of opposite series in the tests of 1 parameter by 3 times compared to the actual historical values.
4. The tests of parameter 1 were applied 32 times in this study (cumulatively for different types of forecasts and price levels), but we did not get one test that occurred in each of these cases, although there are still the most and least frequent ones: 21 times — test 1; 19 times — tests 5, 15, 16; 18 times — tests 10, 14; 17 times — tests 7, 11-13, 19-22; 16 times — tests 6, 8; 13 times — test 4; 9 times — test 9; 3 times — tests 3, 17, 18; 2 times — test 2.

The parameters P2, P3, and P13 have the least influence on the model performance (see Table 1 for a detailed description of the applied parameters in the tests). The moderate influence is exerted by P4, and parameter P9 showed ambiguous results, as it was encountered 18 times in the tests with its fixed value, and only 9 times in the tests with a variable value. In turn, the parameters encountered in more than half of the cases have the greatest influence on the performance of the model: P1, P5-P8, P10-P12, P14, and P15.

Thus, this model's greatest influence on forecasting is the preponderance of weeks with a rising closing price over those with a falling closing price (P1), the preponderance of weeks with a rising MACD histogram over those with a falling MACD histogram (P5), and other MACD-related indicators (P6–P8), as well as most correlation indicators. Contrary to expectations, the impact of maximum and average price movement in the same direction was extremely rare (P2 and P3), occurring only two and three times, respectively. However, the repetition of the MACD histogram movements from the previous week (P9) in the closing prices of the current week supports the conclusions of Ignatenko and Dokienko (2025c) regarding the influence of the previous week's MACD histogram indicator on next week's prices.

In turn, tests of parameter combinations were applied in this study 40 times (in total for different types of forecasts and price levels), but we did not get one combination that occurred in each of these cases, although there are still the most and least frequent ones: 12 times — test 29; 11 times — tests 24-28; 10 times — tests 12, 30; 9 times — tests 11, 19; 8 times — tests 3, 5, 13, 21, 23; 7 times — tests 2, 6, 15, 18, 20; 6 times — test 14; 5 times — tests 4, 10; 4 times — tests 1, 7; 3 times — test 22; 2 times — test 8; 1 time — test 17; 0 times — tests 9, 16.

It is possible to exclude the influence of combinations 9 and 16 (see Table 2 for details), and accordingly, to exclude the influence of parameter P15 and the combination of P1–P4 only. The low frequency of combination 17 (only once) indicates the need to include the parameters responsible for MACD. Similarly, the low frequency of combination 8 (only twice) indicates the need to include correlation in the calculation of predictions; it should have an influential score rather than the score of 0.1 observed in test 7, which occurred only four times.

The most frequent combinations were 12, 24-30, and more than 25% of cases out of 40. Combination 12 has amplification of parameters P4 and P8, and combinations 24-30 are modifications of parameter P5, which confirms its influence. In general, combinations in which the leading role is given to MACD parameters (P5-P8) rather than prices (P1-P4) are more frequent.

CONCLUSIONS

The study produced a forecasting model that demonstrates a higher probability than the actual historical results. The length of unsuccessful forecasts produced by the model is significantly shorter than the range of opposite movements in the historical data series. In some cases, the model achieved 100% accuracy and zero failed forecasts. In general, the performance of the model can be characterized as follows:

1. Forecasts that consider only growth or decline after the initial opposing event are more accurate and have a shorter opposite series than general weekly forecasts that consider growth and decline simultaneously.
2. Forecasts based on combinations of parameters are more accurate and have a shorter opposite series than those based on one parameter. However, one-parameter forecasts produce a greater number of forecasts.
3. For most tests of growth and decline following an initial opposing event, increasing the number of points in the prediction tends to increase the probability and decrease the length of the opposing series. At the same time, the number of forecasts decreases (down to a single event throughout the entire observation period). However, for weekly forecasts, the effect of the number of points on the probability and length of the series is less significant, though the number of forecasts still decreases.

4. There is no universal test that can demonstrate maximum performance for all price levels and forecast types. Therefore, it is more advisable to use it comprehensively in practice, i.e., to monitor the most significant results (P1, P5–P9) and combinations simultaneously (12, 24-30).
5. The model has demonstrated its ability to perform as well as, if not better than, known finite data in the face of unknown finite data, making it widely applicable to predicting the weekly Bitcoin closing price in an unknown future.

In addition, the model is both flexible and scalable. Additional parameters (e.g., stock exchange indicators) can be added to it, and their influence can be calibrated. While the model can be used to calculate the price of any cryptocurrency, not just Bitcoin, using it to calculate the daily closing price requires additional research.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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МОДЕЛЬ ПРОГНОЗУВАННЯ ТИЖНЕВОЇ ЦІНИ ЗАКРИТТЯ БІТКОЇНА

Основною метою дослідження є розробка методологічного підходу до прогнозування тижневої ціни закриття біткоїна з використанням кореляційно-індикаторної моделі. Основними завданнями дослідження визначено: виявити параметри, що здійснюють найбільший вплив на формування прогнозу тижневої ціни закриття біткоїна; установити комбінації параметрів, які дають найбільш точний прогноз, а також установити вплив кінцевих результатів і кількості наданих їм балів на успішність розробленої моделі прогнозування. У дослідженні розглянуто три типи прогнозів: щотижневий прогноз ціни закриття біткоїна, прогноз зростання ціни біткоїна після першої події падіння ціни та прогноз на падіння ціни біткоїна після першого випадку зростання ціни. В основу дослідження покладено щотижневу ціну закриття біткоїна (з розміром вибірки 346 тижнів від 2 квітня 2018 року до 11 листопада 2024 року), індикатор MACD та коефіцієнти кореляції Пірсона між історичними значеннями досліджуваних індикаторів. У ході дослідження була побудована й протестована модель прогнозування щотижневої ціни закриття біткоїна, яка показує ймовірність краще, ніж фактичні історичні результати; тривалість неуспішних прогнозів моделі суттєво нижчі, ніж серії протилежних рухів ціни біткоїна за історичними даними; за деякими тестами отримані 100% імовірності й нульові довжини прогнозів, які не збулися. Загалом, запропонований авторами підхід дозволив виявити параметри та набори параметрів, що мають найбільший вплив на якість прогнозування ціни біткоїна. Практичне застосування запропонованого підходу продемонструвало ефективність кореляційно-індикаторної моделі в роботі й з відомими, і з невідомими кінцевими даними, що сприяє її широкому застосуванню для прогнозування тижневої ціни закриття біткоїна в умовах невідомого майбутнього.

Ключові слова: криптовалюта, біткоїн, ціна біткоїна, прогнозування, модель прогнозування, MACD, трейдер

JEL Класифікація: C53, C58, E47, G17

Table A.1. Single parameter tests.

Test	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
1	1														
2		1													
3			1												
4				1											
5					1										
6						1									
7							1								
8								1							
9									V						
10									1						
11										V					
12										1					
13											V				
14											1				
15												V			
16												1			
17													V		
18													1		
19														V	
20														1	
21															V
22															1

Table A.2. Tests of parameter combinations.

Test	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
1	1	1	1	1	1	1	1	1	V	V	V	V	V	V	V
2	2	2	2	1	2	2	2	1	V	V	V	V	V	V	V
3	3	3	3	1	3	3	3	1	V	V	V	V	V	V	V
4	1	1	0.5	1	1	1	0.5	1	V	V	V	V	V	V	V
5	1	1	1	1	1	1	1	1	V	1	1	1	1	1	1
6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	V	V	V	V	V	V	V
7	1	1	1	1	1	1	1	1	V	0.1	0.1	0.1	0.1	0.1	0.1
8	1	1	1	1	1	1	1	1	V						
9															V
10										V	V	V	V	V	V
11	1	1	1	2	1	1	1	2	1	V	V	V	V	V	V
12	1	1	1	3	1	1	1	3	1	V	V	V	V	V	V
13	1	1	1	1	2	2	2	2	2	V	V	V	V	V	V
14	2	2	2	2	1	1	1	1	V	V	V	V	V	V	V
15	1	1	1	1	1	1	1	1	1	V	V	V	V	V	V
16	1	1	1	1											
17	1	1	1	1						V	V	V	V	V	V
18					1	1	1	1	V						
19					1	1	1	1	V	V	V	V	V	V	V
20	2	2	2	2	2	2	2	2	2	V	V	V	V	V	V
21	1	1	1	1	3	1	1	1	1	1	1	1	1	1	1
22	0.5	0.5	0.5	0.5	3	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
23	0.4	0.4	0.4	0.4	3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
24	0.3	0.3	0.3	0.3	3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
25	0.25	0.25	0.25	0.25	3	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
26	0.28	0.28	0.28	0.28	3	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
27	0.31	0.31	0.31	0.31	3	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
28	0.34	0.34	0.34	0.34	3	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34
29	0.26	0.26	0.26	0.26	3	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26
30	0.24	0.24	0.24	0.24	3	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24

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