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Research Article

Bitcoin Price Prediction with Fuzzy Logic

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ABSTRACT

Due to cryptocurrencies' rising prices, like bitcoin, more and more people are becoming interested in them. Success in this business depends on a good price prediction. Several methods, including heuristic and machine-learning-based ones, can currently estimate the price with varied degrees of success. This study will use the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) model to predict the price's general direction over the next 10 days. Along with popular traders' indicators, the previous day's price will be used. The findings demonstrated that, despite errors, price direction predictions—an increase, a drop, or a stable price—are typically accurate.

1. Introduction

The first decentralized cryptocurrency was Bitcoin, which Nakamoto designed and documented [1]. Over the past few years, cryptocurrencies like bitcoin have emerged as a significant new source of investment. The popularity of cryptocurrencies has skyrocketed since the introduction of the bitcoin in 2008 [1], which has resulted in a significant bloom in business opportunities as well as scams [2], on the market. Bitcoin price was around zero in 2009 then reached nearly $20000 in December 2017 [3]. The highest value it reached in literature so far is about $64000 in November 2021. The current value is now about $26000 in Sep 2023 [4]. Cryptocurrencies are an investment that can be profitable as well as risky. It is vital to forecast their future value in order to boost profit while lowering risk. There have already been a number of publications on the subject that attempted to predict future values across various time periods with varying degrees of success. A Neuro-fuzzy approach is to predict the direction of the change of the daily price of Bitcoin for the next day in [3], and for the stock market trend forecasting with the same methodology again for the next day is studied in [5].

The ability to forecast the four most valuable cryptocurrencies, Bitcoin, Litecoin, Ripple, and Ethereum, using a variety of univariate dynamic linear models and multivariate vector autoregressive model combinations with various types of time horizons (1-7 days ahead) is compared in [6]. In all cases, the multivariate models' success rate for directional predictability is over 50%, with higher percentages of around 60% at the two- and three-day-ahead horizons. All of the models produce quite comparable outcomes. The largest returns are obtained for predicting Ripple, with success rates well above 60%, when examining the directional predictability for each currency separately

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Ethereum, on the other hand, appears to be the currency whose sign fluctuations are the hardest to forecast. Given the significant gains for log score evaluation, it may be possible to continue examining more sophisticated investment methods that place more emphasis on more powerful instances as opposed to just return direction.

There isn't presently a perfect method to predict the future price or trend of a particular cryptocurrency because of how novel the concept is and how challenging the process is. The research is still fragmented, though; some sought to approach the issue by experimenting with various approaches, while others attempted to use diverse data as variables [7–10]. Others attempt to forecast prices for the upcoming hour or the next day [9, 11].

A study describes how the market will be impacted by the present and future Bitcoin movements concerning seven attributes (variables), and a non-linear autoregressive with external input analysis was done [12]. Levenberg-Marquard (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) algorithms were used as three training algorithms to train a neural network. According to a comparison analysis of these three training methods, the BR approach performed satisfactorily and had a low error rate. The proposed initiative will encourage predicting the market trends that affect the Bitcoin market.

The investigation of a theoretical framework for upcoming cryptocurrency research focuses on developing new, sustainable models for the growth of the cryptocurrency industry forecast [13].

Two statistical and three machine learning algorithms are used to forecast the daily price of Bitcoin [14] in a comparison of statistical and machine learning techniques. The simplest method, moving average analysis, which forecasts future values by averaging previous n values, has the biggest inaccuracy. However, for time series analysis, a popular method called ARIMA outperforms the simplest neural network approach. Furthermore, even though setting parameters results in multiple analyses, choosing the optimal ones is not guaranteed. Thus, it is anticipated that nonlinear neural networks outperform ARIMA and other statistical techniques that force data linearization by employing more promising methods for parameter selection from the literature.

The objectives of these studies also tend to differ somewhat. Price fluctuation within a single day or across multiple days may be excessively high. Correctly predicting the price and/or direction could be exceedingly challenging. Before the invention of Bitcoin, a related work about forecasting to model and foresee the realized volatilities for data with very high volatilities was introduced [15].

Several works that use various forms of computational intelligence are available, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Artificial Neural Networks (ANN) [7, 10-11, 16-18]. Some people also combine several Machine Learning techniques, such as Linear Regression and Autoregressive Integrated Moving Average [8], or even the decomposition-composition approach [19] to achieve their objectives.

Other algorithms are developed utilizing some thoroughly researched external data that is not always related. They include the use of economic indicators including the price of gold and crude oil, as well as the EUR/USD, CNY/USD, and JPY/USD exchange rates [7]. Studies have also been conducted both on the economical and technical aspects of bitcoins, such as the difficulty of mining, hash rate, the volume of transactions, or the overall quantity of bitcoins in existence [20]. Additionally, some people analyze, compare, and parallelize the use of many cryptocurrencies, such as Ethereum or Litecoin [8, 19].

In contrast, we make an effort to predict the price trend of Bitcoin 10 days in advance using only its current and historical prices. As we will go into more detail below, we looked into several trading indicators, including the Bollinger Bands and Moving Average. After that, we experimented with a variety of values, including the price at the start and end of the day, as well as the highest and lowest prices that occurred on that day. Then, we tested several combinations while utilizing the ANFIS model suggested by Matlab until we got a good outcome. The combination we ultimately chose yielded a respectable outcome for forecasting the direction but is less than ideal for predicting prices.

However, part of the literature makes use of the average between the highest and lowest price, or even all four values at once. Averaging smoothes the peaks that can cause high errors in price forecasting and misleading the trend. We studied some of these indicators before deciding which one to use.

Actually, we are estimating the derivative of the price function by using the relative price fluctuation. That includes positive and negative values, denoting price rises and declines, respectively. Therefore, rather than focusing on the magnitude of the fluctuation, the goal would be to determine its direction. As long as we can predict when the price is rising, declining, stationary, or reaching an extreme, we may say that our outcome is appropriate. Currently, our greatest strength is our ability to predict the ascent and decline of the price 10 days in advance. This will present a significant window of opportunity for planning ahead and give investors enough time to boost their profits even further. Utilizing key stock market directional indicators like the Directional Movement Index, Bollinger bands, Moving Average Convergence/Divergence, and the Ichimoku Cloud is another contribution of our work. Section 2 provides more information.

The estimated and predicted percentages diverge by an average of 7%, highlighting the stark contrast between the outcomes. Given that the forecasted price's permitted +/- 10% range lies between 90% and 110%, our 7% precision error is still within this range.

Though the outcome from the error in the price forecasting direction has a higher inaccuracy than the price prediction when considering. Typically, there is only a 12% error in the price's direction.

When forecasting the future, models with a 10% error range offer a strong enough degree of flexibility to account for potential extreme volatility, which is a feature of cryptocurrencies. If not, the prediction would be overfitting, which typically occurs in artificial neural network modeling for the given data set, and it would not be effective for abrupt and volatile price fluctuations. In this regard, ANFIS is advantageous to use for predicting work due to the adaptive and flexible nature of fuzzy logic modeling.

2. Modelling

It is possible to find on the internet the daily price value of the bitcoin on the market from 2015 up to today [21]. This data typically includes four values: the price at the beginning and ending of the day, as well as the highest and lowest price reached that day. Typically, when creating additional indicators, the closing price is used. Figure 1 shows the daily closing price of 2500 days of Bitcoin.

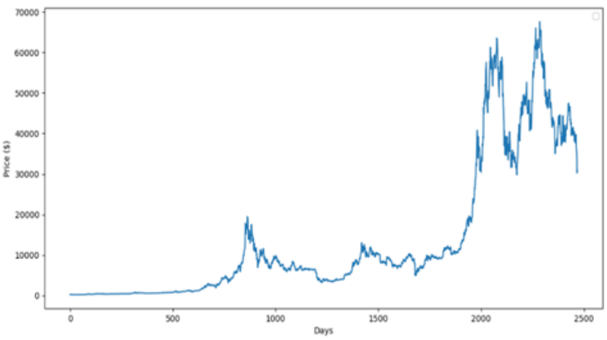

Figure 1. Daily closing price of Bitcoin, from 2015-08-07 to 2022-05-10

However, some researchers use the average between the highest and the lowest price, or even all four values at once [14]. We studied some of these indicators before deciding which one to use.

2.1 Moving averages

The first, basic, indicator is the Moving Average. Simply said, it smooths the daily value using the prices of previous days. While these are extremely useful for removing noise, they are also used to insert some latency, notably when a change of direction occurs.

The simplest among them is the Simple Moving Average (SMA). It simply averages the daily value on a given time frame, with each price having the same importance. As it is simple to calculate, it is frequently used by other indicators as well. Figure 2 shows the bitcoin daily closing price with the averages (SMA, EMA, DEMA) calculated for a 10-day period.

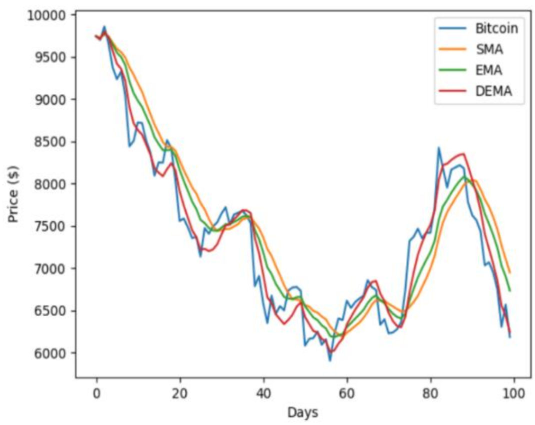

Figure 2. Moving average with a 10-day period

The formula used is (1), where p is the period and v is an array of daily values, with the 0th entry representing the value for the current day.

$$SMA_p(v) = \sum_{j=0}^{p} \frac{v_j}{p} \quad (1)$$

The other Moving Average is the Weighted Moving Average (WMA). The daily values are weighted inversely proportionally to their distance from the searched day. Simply said, the values of the given day have the highest weight, while the farther it is, the less weight it becomes (2).

$$MA_p(v) = \frac{\sum_j^p v_j \cdot \frac{p-j}{p}}{\frac{p\cdot(p+1)}{2}} \quad (2)$$

Another common Moving Average is the Exponential Moving Average (EMA) (3) and (4). The daily value is calculated recursively by adding the weighted value of the day with the complementally weighted EMA of the previous day. The important point is to choose an appropriate weight value, which is typically dependent on the desired period. We are using in our case the weight value as $1 - \sqrt[period]{0.135}$

$$EMA_p^i(v) = v_i \cdot k + EMA_p^{i+1}(v) \cdot (1-k) \quad (3)$$

$$EMA_p^p(v) = SMA_p(v) \quad (4)$$

There are some other variations of the EMA, such as the Double Exponential Moving Average (DEMA) given in (5), or the Triple Exponential Moving Average (TEMA) given in (6), which use the value of the EMA as input for the EMA formula. However, since the EMA is calculated using an interval, taking the EMA of the EMA requires calculating the EMA of every day on the interval first, which rapidly increases the required calculations. As shown in Figure 2, the EMA gives a value closer to the initial one than the SMA, and the DEMA an even closer one, while still ignoring the smallest disparities.

$$DEMA(v) = 2 \cdot EMA(v) - EMA\big(EMA(v)\big) \quad (5)$$

$$TEMA(v) = 3 \cdot EMA(v) - 3 \cdot EMA(EMA(v)) + EMA(EMA(EMA(v))) \quad (6)$$

2.2 Relative strength index and bollinger bands

Among the other studied indicators, there are two of them that are quite useful and easy to understand: the Relative Strength Index and the Bollinger Bands.

The Relative Strength Index (RSI) is obtained by summing up the amount of increases and decreases over a given period of time, and then dividing the amount of increase by the sum of the two. This gives us an idea of the general direction of the price. If the value is greater than 0.5—50 in Figure 3 since we are using percent—this means the increases are more important than decreases in the time interval, signifying the price has increased as a whole. Using several RSI of different periods is useful to notice local protuberance on an overall trend. For example, in Figure 3, which uses the same data as Figure 2, we can notice an overall decrease in the price using the RSI 30, but still notice the small lump around days 30 using the RSI 10. We are also using the DEMA of the RSI in order to have a cleaner output, as we can with the RSI 10 around day 50.

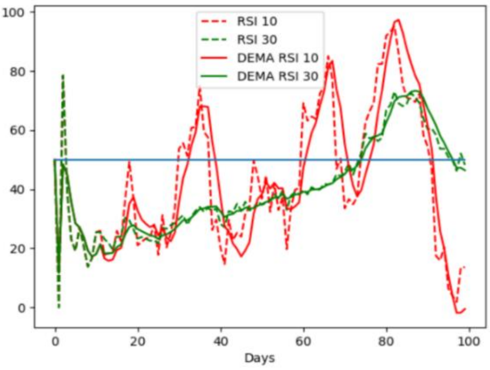

Figure 3. RSI of the price of Figure 2

The other really interesting indicator is the Bollinger Bands (BB). They are composed of three bands: a middle one using a traditional SMA, as well as an upper and lower band created by respectively adding and subtracting twice the standard deviation. The main advantage of the Bollinger Bands is that it visually combines several information, such as the average value with its internal band, the strength of the recent variation by looking at the spacing of the external bands, as well as the current trend by comparing the value with all three bands. This can also be used to normalize the price value by encompassing it between the two bands, as shown in Figure 4. In this case, we are using the delay induced by the SMA to get a hold of the price trend.

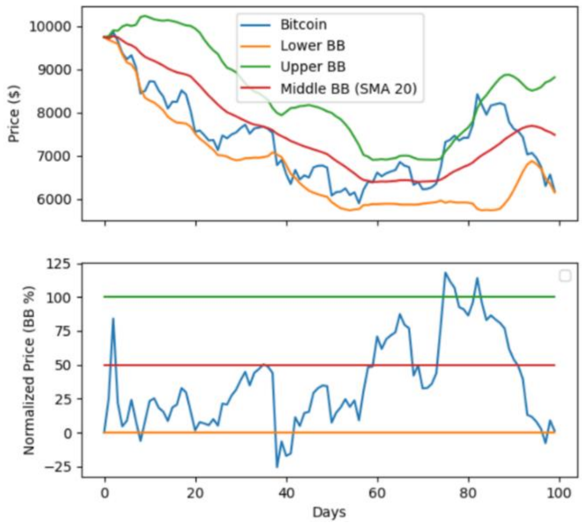

Figure 4. Bollinger Bands with a 20-day period

2.3. Other indicators

Without entering too much detail, we also studied three other indicators called the Moving Average Convergence/Divergence (MACD), the Directional Movement Index (DMI), and the Ichimoku Cloud.

The MACD is calculated using three periods, typically one small, one medium, and one large. A first line is created using the difference between the medium and large period EMAs, and a second line is obtained with the EMA of the previously created line over the small period. The MACD indicators used the small delay added by the moving average to determine an upper or lower trend, as well as a turning point, by taking the difference between the two previously created lines, as shown in Figure 5.

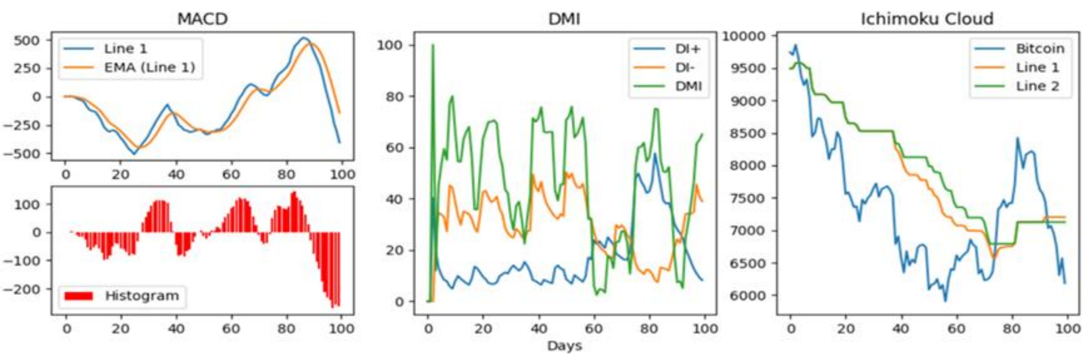

Figure 5. Example of MACD (9,12,26), DMI (20) and Ichimoku Cloud, on the same interval

3. Formulation

The DMI, much like the RSI, uses the difference in the prices. Unlike the RSI, it will calculate the increase using the highest daily value and decrease with the lowest daily value. Eventually, the DMI is obtained by dividing the absolute difference of the two by their sum, while adding some normalization to the process. The DMI focused more on pointing out the strength of a variation rather than its direction, which is an excellent complement to the RSI.

The Ichimoku cloud is without any doubt the most obscure indicator that we studied. The cloud mentioned in the name is the space comprised between two lines obtained using relatively old data. The first line is created by averaging two SMAs of different periods from the past, i.e., a short one, around 1 week, and a longer one, around 1 month, from several days ago, generally another month. The second line uses the current SMA for the longest period covered by the previous curve, so typically around 2 months. Good traders may be able to extract lots of information from the Ichimoku cloud, similarly to how the Bollinger Bands can be used but seems to be more prone to the rule of thumbs than actual logic.

By utilizing all of the aforementioned indicators, we attempted to predict the price in the future. In addition to the codes we prepared, we elected to use the ANFIS technique on the MATLAB platform. Using a few inputs and their anticipated outcomes, ANFIS enables us to automatically create a Neural Network System, which is a compressed form of artificial intelligence.

As the name implies, ANFIS uses a fuzzy approach by assigning a membership function to each input variable and then adaptively creates the model for the provided data set to produce an output. A fuzzy system typically has three steps: first converting a numerical (crisp) input into a fuzzy input, then using the fuzzy inputs to infer with the rules defined and produce a fuzzy output, then converting the fuzzy output into a numerical value.

During the first step, which is called fuzzification, the numerical values are converted depending on their accuracy relative to some vaguer value by choosing an appropriate membership function for each input variable.

The second step, inference, involves applying fuzzy arithmetic to various combinations of the inputs to get an output that complies with certain rules (if-then rules, reasoning) by utilizing expert knowledge as well.

Following the inference, the ANFIS model has an additional step that assigns weights to each output. Each rule has a particular weight; therefore, the weighting process depends on both the original input and the rule. The formula used for weighting is given in equation (7):

$$weighted = inferred\left(w_{rule} + \sum_i w_{in_i} in_i\right) \quad (7)$$

where w stands for weight and in for inputs. ANFIS will adjust the weights over multiple iterations of trials and errors until the output is sufficiently near the expected one.

In the third step, defuzzification, we aggregate the results of every rule output and then perform the rules of defuzzification. The fuzzy system, as shown in Figure 6, converts them to a single numerical value, crisp output.

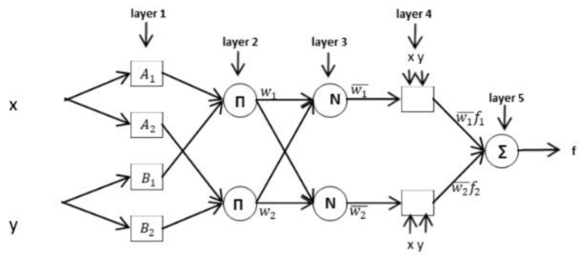

Figure 6. ANFIS structure [22]

The ANFIS plugin can be found on MATLAB's applications under the name Neuro-Fuzzy Designer. The input data file is prepared as follows to get the data ready for ANFIS to train the data and then build a model: the first to (n-1)th columns of the array will be input variables, and the last column of the array nth will be output variables. Once the data are loaded, the number of inputs are inferred with the rules defined, and it becomes possible to generate the Fuzzy Inference System (FIS). By selecting Grid Partition for the generation, we can specify for each input the number of fuzzy membership functions we want, as well as their shape. In our case, we are using four Generalized Bell (gbell) function as inputs, with a linear output. Once the FIS is generated, the last step is to train it using the inputted data. We trained our FIS a total of 13 iterations since we noticed it to be the optimal number of iterations in error-wise.

One thing must be noted. One rule will be generated for every combination of the membership functions of every input. This means that four inputs with three membership functions generate 3^4=81 rules in total, but with six inputs, we already reach 3^6=729 rules. With that much, we need a huge amount of data for training, as well as a lot of time for it to be performed. For that reason, we have decided to limit ourselves to a maximum of four inputs, greatly reducing our possibilities of input.

Moreover, because of the high fluctuation of the bitcoin price, our data are very heterogeneous, as seen in Figure 1. Our initial price is of the order 10^2, which was around 10^3 after a few years and reached 10^4 a few years ago. For that reason, it is not possible to train our algorithm using actual values; the difference in the order of the price would forbid us to effectively train our FIS. We need to transform them into something that is stable—or at least consistent—over time. We did try to use the added value compared to the previous day, but the resulting data was as fluctuating as with the initial one, as seen in Figure 7. Therefore, we moved to the use of relative value. That is, instead of using the flat difference in the price compared to the previous day, we use the added percentage of it. This gives us new data way more consistent, varying between plus and minus twenty with some isolated peaks throughout the whole dataset. An equivalent method needs to be applied to some indicators as well in order to normalize them and obtain once again consistent data.

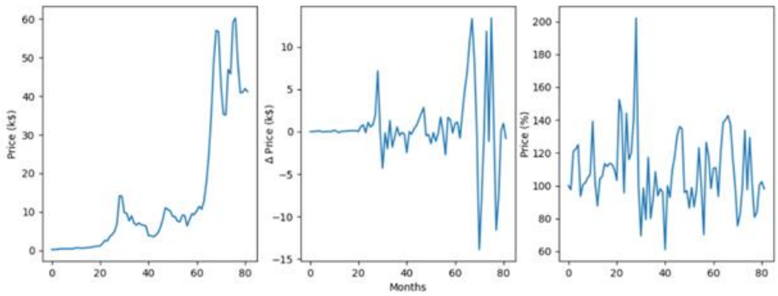

Figure 7. Difference of interpretation of monthly Bitcoin value

3. Results and Discussion

After several combinations of the previously described indicators, we set our minds over the combination of the three following indicators: the daily closing price relative to the average closing price over 10 days (v_0/SMA_10 (v)), the position of the daily closing price relative to the Bollinger Bands of 20 days (BB20 normalized price), as well as the ratio between the upper and lower Bollinger Bands. As for the output, we decided to use the average closing price for the upcoming 10 days over the average closing price covering the past 10 days ($SMA_p(v_{-p,})/SMA_p(v)$).

We tested it over three samples of data, as shown in Figure 8. The first dataset includes data from 2022-01-31 to 2022-05-10, both included. The second dataset is from 2022-05-10 to 2020-12-27 again, while the third one is also part of the training datasets, located between 2018-05-03 and 2018-08-10.

The percentages estimated and expected differ by an average of 7%, which highlights the results' significant disparity. Given that the allowable +/-10% range for the predicted price falls between 90 and 110%, our 7% precision error remains within this range.

However, when looking at the error in the direction of the price, the result is not as good as the price forecasting. If we exclude the 98-102% range since we can consider it the stagnation price range, and count the number of times the calculated and expected values are on different sides of the 100% line, there is on average only a

Table 1. Comparison of existing techniques for cryptocurrency and stock market price forecasting.

Paper	Year	Objective	Methodology	Data type	Forecast duration	Cryptocurrency	Results
3	2019	Forecasting direction in the change of the daily price of Bitcoin	Hybrid neuro-fuzzy controller, two ANFIS sub-systems, PATSOS, buy-and-hold	Closing price	Next day (1 day ahead)	Bitcoin, Ethereum, Litecoin, Ripple	Accuracy: %71,21
5	2009	Prediction of stock market short-term trend	Hybrid neuro-fuzzy controller, two ANFIS sub-systems, PATSOS, buy-and-hold	Closing price	Next day (1 day ahead)	Stock market	Accuracy: %68.33
6	2019	Comparison of univariate and multivariate models for point and density forecasting	Univariant and multivariant models, density forecasting, dynamic model averaging	Closing price	1 to 7 days ahead	Bitcoin, Ethereum, Litecoin, Ripple	Accuracy: %60
7	2021	Forecasting price of Bitcoin	ANFIS	Closing price		Bitcoin	RMSE: %8.4
8	2020	Forecasting price of Bitcoin	Machine learning, time series analysis	Closing price		Bitcoin, Ethereum, Litecoin, Zcash	
9	2021	Predict short-term price movement of Bitcoin market	Machine learning		5-min, 15-min, 60-min	Bitcoin	Accuracy: above %50
11	2017	Predict the next day the direction of the price of Bitcoin	ANN ensemble approach called Genetic Algorithm-based Selective NN Ensemble		Next day	Bitcoin	Accuracy: %58-%63
12	2021	Attribute selection and Trend analysis of Bitcoin	Non-linear Autoregressive with External Input analysis with seven attributes, NN-based LM, BR, and SCG algorithms	Price, Volume, Market cap, Social dominance, Development activity, Market value to realized value, Realized cap	Next value	Bitcoin	LM R:0.65751 BR R:0.59395 SCG R:0.65589
13	2020	Analysis and prediction of the growth of the cryptocurrency market	Pool complexity approach to choose the optimal technology, EOS network structure	social activity on the internet, trading parameters		Bitcoin, Ethereum	
14	2021	Forecasting price of Bitcoin	Statistical analysis, MVA, ARIMA, and Machine Learning, DNN, RNN, CNN,	Closing price, Average (previous n-values)	Next day	Bitcoin	MAPE: 1-layer, ANN:4.05 3-layer, ANN:3.84 CNN:3.75 RNN:2.70
18	2020	Forecasting price of Bitcoin and Ethereum	NN analysis, Backpropagation, Radial bases function, Extreme learning machine, Long-short term memory	Opening price		Bitcoin, Ethereum	Bitcoin RMSE ELM:25.8 RBF:31.31 ANFIS:31.3 BP:18.52 LSTM:17.8
19	2020	Develop a novel approach for modeling and analysis of the cryptocurrency prices	Two-stage decomposition and composition method (2SDC)	Daily closing		Bitcoin, Bitcoin cash, Ethereum, Litecoin, Monero, Dash	

12% error of direction of the price. It can be noticed that the findings are better when compared to the data in Table 1 than the literature review.

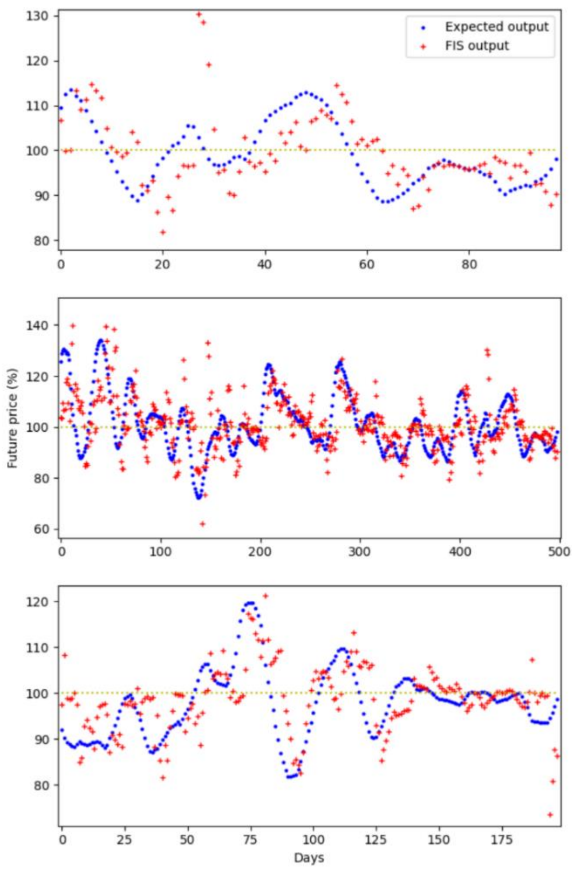

Figure 8. The expected result compared to the obtained result, ANFIS simulation results.

By utilizing the relative price variation, we are in fact estimating the derivative of the price function. Positive values are produced by price increases, while negative values are produced by price decreases. Therefore, determining the direction of the fluctuation rather than its magnitude would be the key factor. We can consider our outcome to be appropriate as long as we can anticipate when the price is rising, falling, stagnant, or reaching an extreme. The ability to identify rise and decline is currently our greatest strength. However, the current version is unable to detect an extremum accurately, which is discovered while the price is already declining.

4. Conclusion

Eventually, we were able to create a prediction algorithm that was only based on the price of bitcoin. We successfully developed a model that ANFIS can use since we are able to adjust our data.

As a result, it has successfully created a system capable of making predictions. Even though the results are far from perfect, accuracy is still a respectable 88% percent with a 12% error, which is better than the findings of the literature review displayed in Table 1.

We did have a few issues even though we were able to forecast the price. First of all, the enormous data disparity makes the entire prediction process challenging. Predicting the future price while considering the current value is difficult, both computationally and from a human perspective. In fact, there appears to be no pattern as the price fluctuates sharply from time to time. The major reason is that the price is determined by external circumstances, in this case, excessive purchases and/or sales, rather than adhering to a straightforward or even complex formula.

The ANFIS input limit was another issue that we did run across. The capabilities of ANFIS limited us. The number of rules is greatly increased by expanding the dataset, adding more input variables, and using more membership functions. This barrier could be removed or at least decreased, but not entirely, leading to an increase in computing complexity or longer processing times. We could only use four variables at once or three of them due to the limited amount of data we could gather simultaneously. Of course, we could have used more variables if we had manually set the requirements and the required signs. The testing and planning stages, however, would have taken a very long period. As a result, we may say that ANFIS is not the greatest instrument for making these kinds of forecasts.

However, when forecasting, models should provide some degree of error freedom and enough degree of flexibility to account for potential extreme volatility, which is a feature and nature of cryptocurrencies. If not, the prediction would be overfitting, which typically occurs in artificial neural network modeling for the given data set, sometimes measured data and predicted data fitted one-to-one and it would not be effective for abrupt and volatile price fluctuations. In this regard, ANFIS is advantageous to use for predicting work due to the adaptive and flexible nature of fuzzy logic modeling.

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The Declaration of Ethics Committee Approval
This study does not require ethics committee permission or any special permission.

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The authors of the paper declare that they comply with the scientific, ethical, and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification of the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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