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Bitcoin prediction with a hybrid model

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ABSTRACT

. In recent years, Bitcoin has become the most widely used blockchain platform in business and finance. The goal of this work is to find a viable prediction model that incorporates and perhaps improves on a combination of available models. Among the techniques utilized in this paper are exponential smoothing, ARIMA, artificial neural networks (ANNs) models, and prediction combination models. The study's most obvious discovery is that artificial intelligence models improve the results of compound prediction models. The second key discovery was that a strong combination forecasting model that responds to the multiple fluctuations that occur in the bitcoin time series and Error improvement should be used. Based on the results, the prediction accuracy criterion and matching curve-fitting in this work demonstrated that if the residuals of the revised model are white noise, the forecasts are unbiased. Future work investigating robust hybrid model forecasting using fuzzy neural networks would be very interesting.

Keywords: Exponential Smoothing, ARIMA Model, ANNs, Combination Forecast, Optimization, Robust Predictions.

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1. Introduction

In recent years, there has been an increasing interest in Forecasting economic and financial time series data is a challenging task due to uncertain events or incomplete information in the economies in which we live. The volatility in time series is high in this situation. Authors have over time applied increasingly sophisticated predicting techniques to predict it more accurately. The most common cryptocurrency in the world is Bitcoin.
Since Bitcoin values are highly volatile, we need to use a robust model. Using many different approaches on the same time series and averaging the resulting predictions is a simple way to increase forecast accuracy. John Bates and Clive Granger wrote a famous paper, showing that combining forecasts often leads to better forecast accuracy. In recent years, Clemen wrote that it is almost universally agreed that integrating numerous forecasts improves forecast accuracy. By merely averaging the projections, one may often increase performance dramatically. Time series forecasting may also be done using ARIMA models. The two most generally used techniques for time series forecasting are exponential smoothing, ARIMA, and artificial neural network models, which provide complementary approaches to the problem. ARIMA models try to characterize the autocorrelations in the data, whereas exponential smoothing methods are based on a description of the data's trend and seasonality.
Artificial neural networks (ANNs) are one of the non-linear models and is the foundation of artificial intelligence (AI). It has the property of self-learning and adaptation. Research efforts on neural networks as forecasting models are commendable, and many studies have reported on the use of ANNs for forecasting. Although some theoretical and empirical issues remain unresolved, the field of neural network forecasting has unquestionably advanced over the last decade. It is not surprising that the next decade will see even more progress and success.

Studies relating to predicting Bitcoin have been relatively scanty (few) and there is no study focusing on the hybrid model [1], [3], [6], [13]. Previous studies have primarily concentrated on Comparison between traditional (exponential smoothing, ARIMA) and modern models (artificial neural network ANN) of forecasting methods to determine the best model, without interest in the fluctuations in time series behavior that may arise in the future [4,6,7,9,12,14,17].

The contribution of this study is obvious as the resulting outcomes can be capitalized as guidelines for Comparison between traditional and modern models of prediction methods.

This paper is the well-known implementation of actual data collected from the period January 2018 to February 2021, which is the closing price data for Bitcoin (digital currency). This paper is divided into five sections: introduction (the objective of the study, and literature review), theoretical, implementation, analysis, and conclusion.

2. Method

2.1. Exponential smoothing model

Exponential smoothing is a method for forecasting time series based on univariate observations that can be applied to data with a systemic trend or seasonal compound. It is a strong method of forecasting that can be used as an alternative to the common Box-Jenkins ARIMA family of methods[1]–[4].
To forecast data with trends, Holt expanded single exponential smoothing to linear exponential smoothing with trends. Holt's linear exponential smoothing consists of two constants, α and β (with values between 0,1), and three equations [2,8,13]:

$$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + b_{t-1}) \qquad (1)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \qquad (2)$$

$$F_{t+m} = I_t + b_t m \qquad (3)$$

Where:
y_t= time series
L_t: Estimation of the time series level at time t.
b_t : An estimate of the slop time series at time t.
F_{t+m} : forecast at time $t+m$.

2.2. Optimization

The majority of exponential smoothing techniques need the definition of several smoothing parameters (constant). These determine how quickly the forecast reacts to changes in data. Because the computer time required to optimize these parameters was so costly, methods involving more than one or two parameters were seldom employed, and parameter values were limited to a narrow number of options[2], [5]–[7]. With the introduction of considerably quicker commutes, choosing a nonlinear optimization technique to optimize parameters is rather simple. All competent forecasting software will automatically optimize parameter values[2], [5], [8]–[12].

2.3. ARIMA model

A variable's future value is supposed to be a linear function of many past observations and random errors in an autoregressive integrated moving average model. As a result, a nonseasonal time series can be modeled as a mixture of past values and errors, which can be expressed as ARIMA (p,d,q) or as follows [1], [3], [6], [13]:

$$\emptyset(B)(1-B)^d y_t = \theta(B) \in_t \qquad (4)$$

Where:
y_t : is the time series

$\in_t$: error
B: backward shift operator.
p: order of the autoregressive part.
d: a degree of first differencing involved.
q: order of the moving average part.
Figure 1 illustrates the methodology for the ARMA model

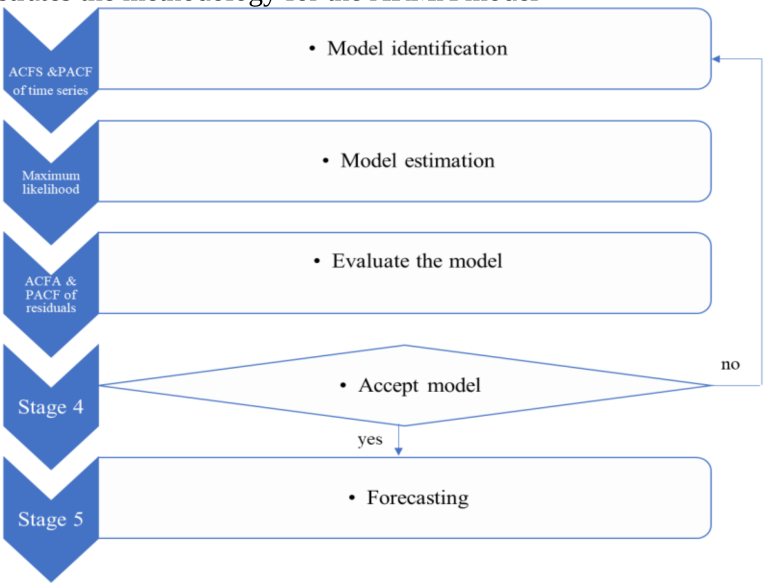

Figure 1. ARIMA model methodology

2.4. Artificial neural network

An artificial neural network (ANN) is a computing framework inspired by a biological neural system and is made up of small, interacting processors known as neurons. Weighted connections bind the neurons, allowing signals to flow through them. Each neuron receives multiple inputs proportional to its contact weights from other neurons and produces a single output that can be propagated to multiple other neurons. An artificial neural network is capable of learning and generalizing relationships in a data set, as well as providing fast and accurate estimates.
In computing applications, the Back Propagation Neural Network (BP) is the most widely used neural network technique. It's a multilayer artificial neural network (ANN) with a feed-forward connection from the input layer to the hidden layers and finally to the output layer. The BP algorithm aims to reduce the mean square error between the forecast and desired outputs. Figure 2 shows the structure of the BP [8], [9], [14]–[17].

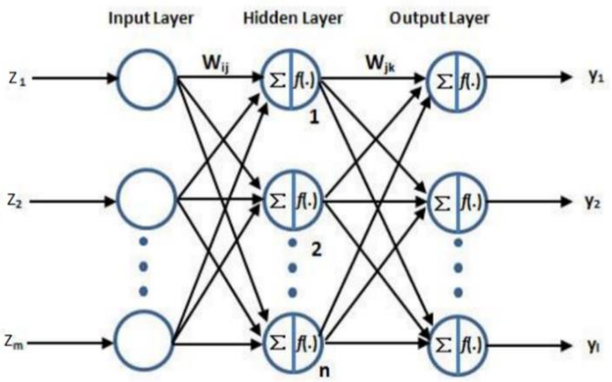

Figure 2. BP structure

2.5. Forecast's combination

Combining data enhances predicting accuracy without a doubt. This empirical observation holds when it comes to statistical forecasting, judging estimations, and averaging statistical and subjective forecasts. Also. Combining results in a significant reduction in the variance of post-sample forecasting inaccuracy. The empirical findings contradict the statistical theory, requiring a reassessment of what constitutes effective forecasting methods and how they should be used [2], [3], [5], [6], [17].

Forecasting is combined as well as the best mix of forecasting. Furthermore, the root means square error (RMSE), which measures the variance or level of uncertainty in our forecast, is lower with a simple combination than with either the individual approach or the best combination. The rationale for this is that the average reduces the RMSE by canceling big prediction errors. The fact that a simple combination decreases the RMSE of the post-sample forecast is another incentive to use it in reality; reduced error equals less uncertainty, which translates to smaller inventories and, thus, minimizes costs [9], [14], [18].

2.6. Measuring forecast accuracy

In most forecasting situations, accuracy is treated as an overarching criterion for the selection of the forecasting method. In many cases, the word 'accuracy' refers to 'goodness of fit,' which in turn refers to the extent to which the forecasting model can reproduce the data already known to the forecast consumer. The accuracy of the future forecast is the most important thing. The most common measure of error accuracy is [1], [13], [19]:

Root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_t - f_t)^2}{n}} \qquad (5)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{y_t - f_t}{y_t}} \qquad (6)$$

$$R^2 = 1 - \frac{RSS}{TSS} \qquad (7)$$

Where:
n: number of observations (number of non-missing data points)
y_t: Actual value
f_t: forecast value
R^2: coefficient of determination
RSS: sum of squares of residuals.
TSS: the total sum of squares.

3. Results and discussion

Figure 3 presents the time series from 1/1/2018 to 18/2/2021 for bitcoin's daily closed price (Source data: the wall street journal website).

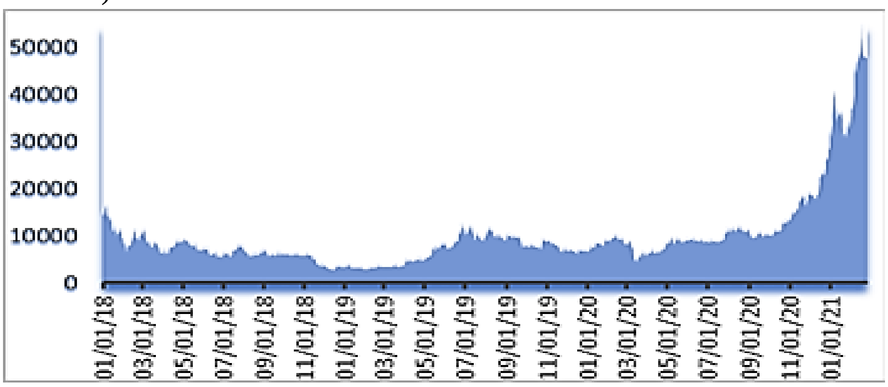

Figure 3. Closed price bitcoin series

As shown in Figure 3 there is a clear trend in time series, the closed price of bitcoin is rising significantly between the end of 2020 and the end of 2021, with a slight decline at the end of February. Because of the high level of volatility in the market, such as during the COVID-19 pandemic, there is inconsistency in the actions of the bitcoin closing price sequence. The following are the forecasting methods' findings for the time series under study:

3.1. Exponential smoothing model result

Figure 3 illustrates the series has a linear trend, so the best model is Holt's linear exponential smoothing. Use a statistical program (V.12) to find optimal parameters, and the results are as follows.

Table 1. Optimal parameter of Holt model

Optimal parameter	estimate
α	0.98
β	0.18

The results of the evaluation of this model were as follows:

Table 2. Model fit statistics of Holt model

Model Fit statistics		
R^2	RMSE	MAPE
0.994	600.864	2.63

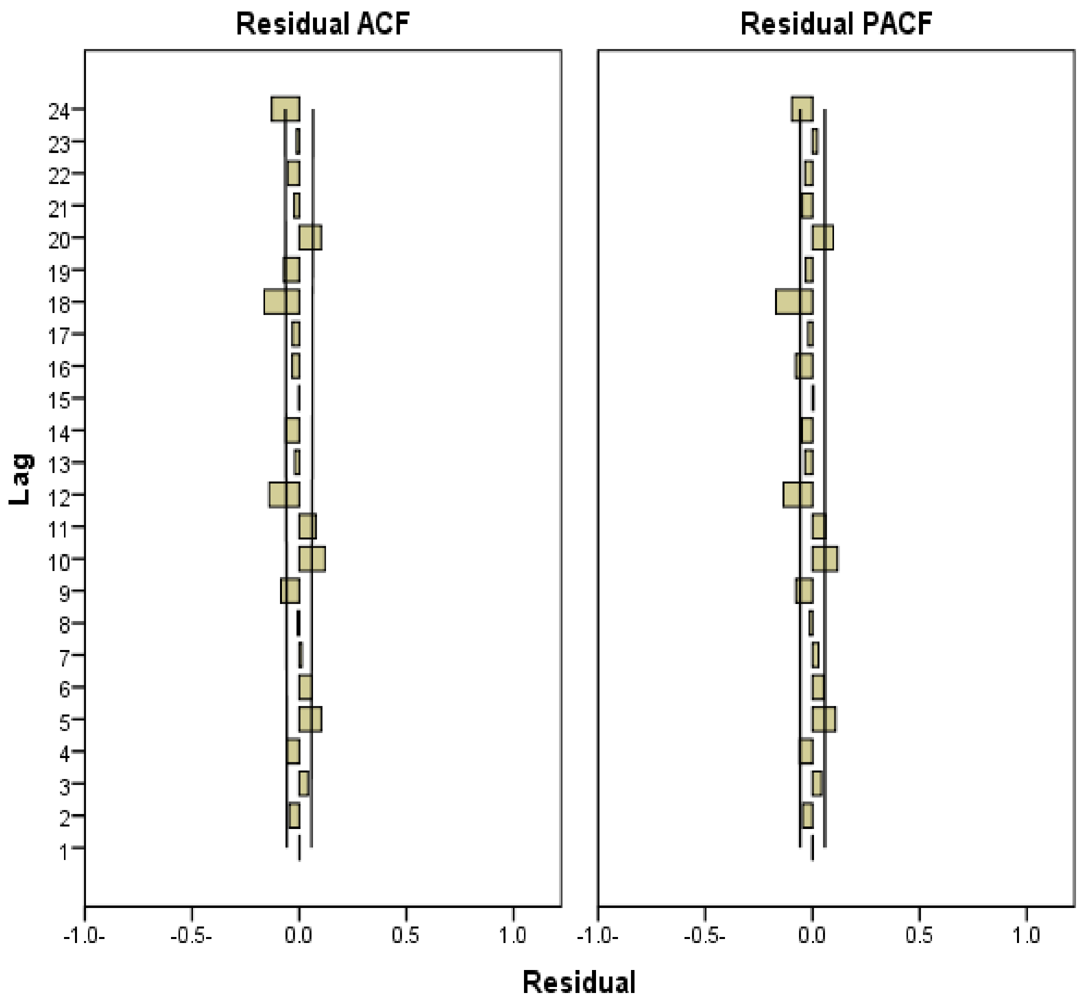

Figure 4. Autocorrection and partial Autocorrection function for residual

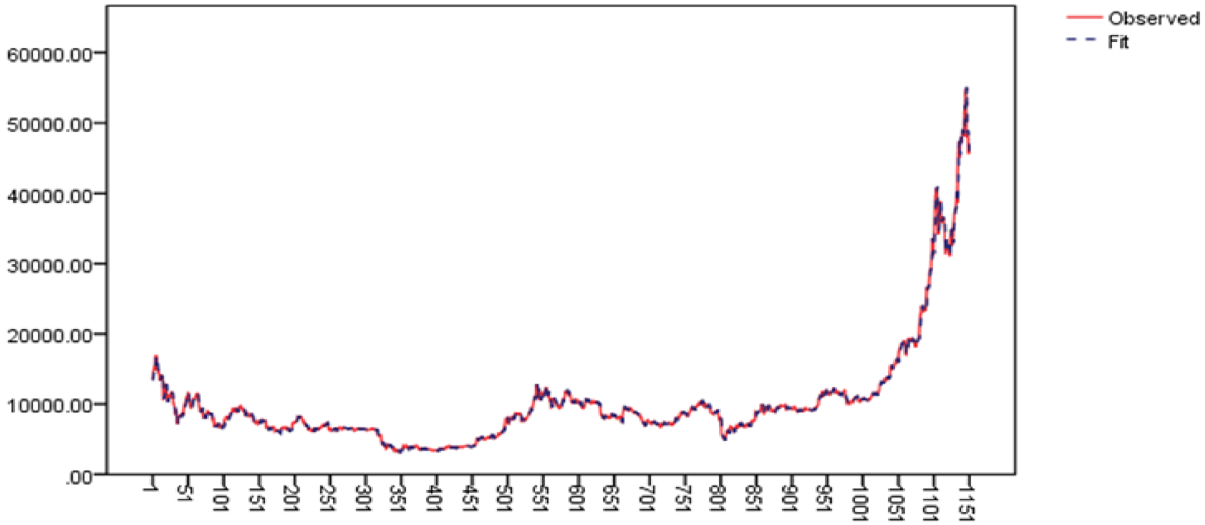

Figure 5. Curve fitting of exponential smoothing model

The finding of the present study suggests that It is clear from the result that significant parameter and the ACF and PACF coefficients of the residues is random behavior and white noise. This model is appropriate and the best.

3.2. ARMA model result

The best ARIMA model for the time series under research is ARIMA (1,0,0), based on the analysis of ACF and PACF. The ARIMA model was computed using SPSS (V.23), and the model parameter estimates are shown in Table 3.

Table 3. ARIMA model parameters

Estimate	SE	t	Sig.
0.96	.002	634.324	.00

The results of the evaluation of this model were as follows:

Table 4. Model fit statistics of ARIMA model

R^2	RMSE	MAPE
0.994	605.626	2.64

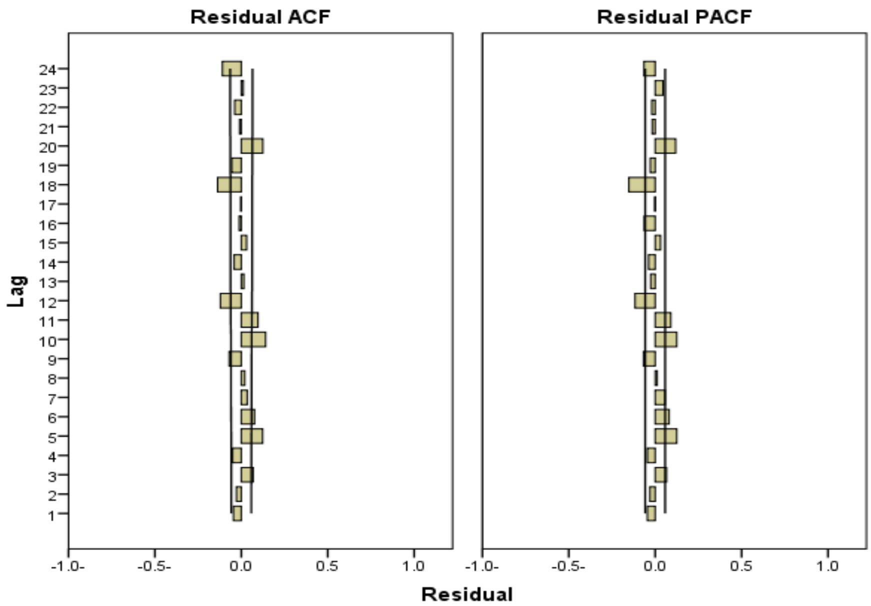

Figure 6. Autocorrection and partial autocorrection function for residual

Figure 7. Curve fitting of ARIMA model

Thus, the mathematical model of the ARMA model is according to the following formula

$$y_t = 0.99\, y_{t-1} + \epsilon_t \qquad (8)$$

The findings suggest that It was found that the ACF and PACF of the residuals are random behavior and white noise. and the significance of the Ljung-Box test, the estimated model is the best.

3.3. Artificial neural networks

MATLAB was used to provide the following results for the time series under Search from the BP:
Input Layer: this layer has one node, which is represented by the variables y_{t-1}, with a one-degree time series lag. Hidden layer: The maximum number of nodes in this layer is 15, and there is only one layer (after several trials). the output layer consists of only one node, which is represented by the y_t vector. Figure 3, and 4 shows the performer's performance for the BP network for the time series under consideration. Table 2 shows the results of the error evaluation by comparing the two methods used.

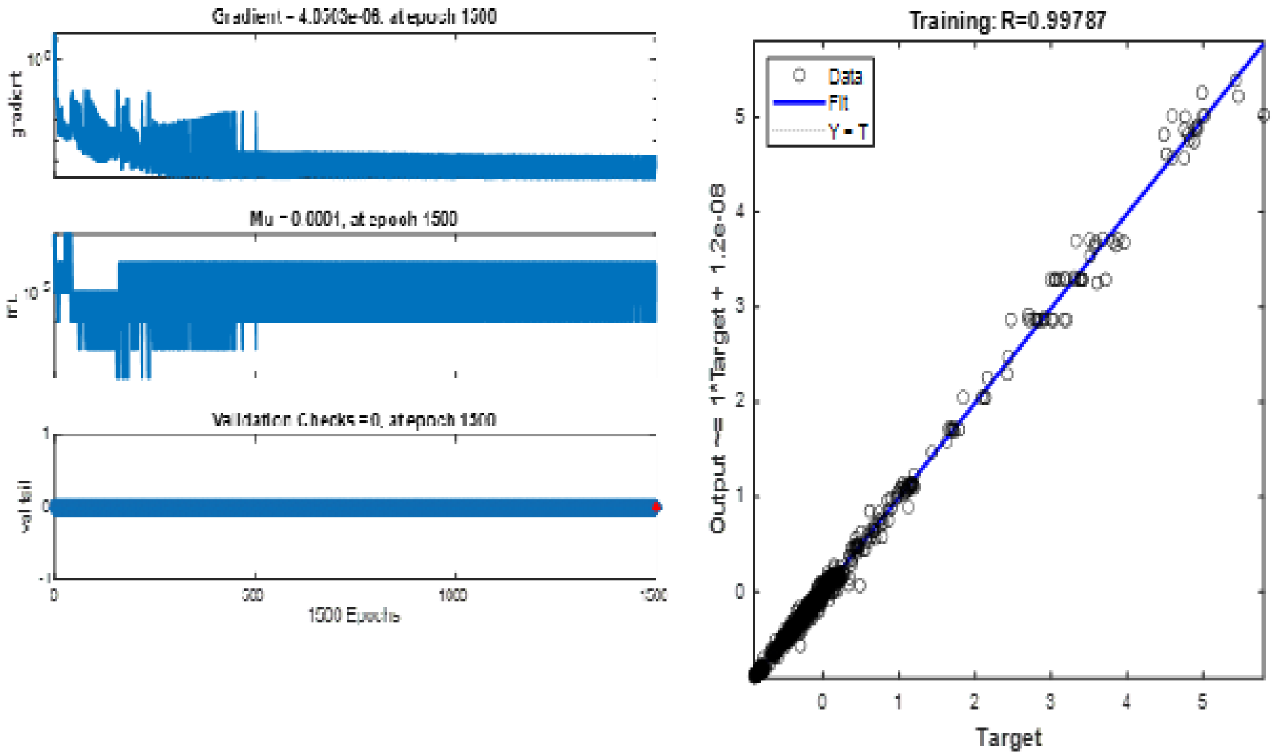

Figure 8. Performance of ANN

Time series response and the response of output element for time series are shown in Figure 8.

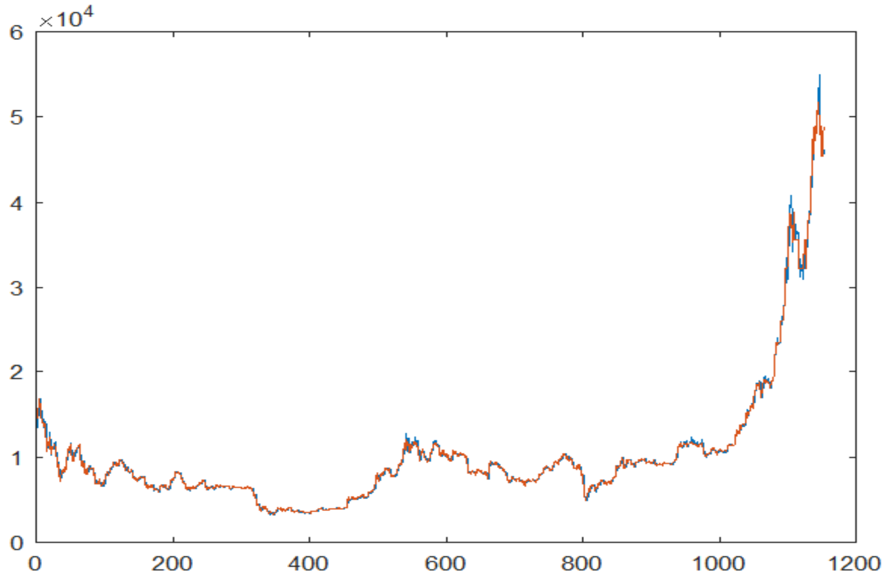

Figure 9. Curve fitting of ANN

Table 5. Accuracy error of ANN model

R^2	RMSE	MAPE
0.997	502.95	2.53

From the data in Figure 8, it is apparent that Network evaluation results are significant. It appears from Table 1 that, the error accuracy results are good.

3.4. Combination model result

In this section two combination models will be used, the first includes the traditional models only and the second includes the traditional and modern models.
Model I
The first model includes ARMA and exponential smoothing based on the error weight of each model. Therefore, the mathematical model is as follows:

$$c_{t+1} = w_1 ARIMA(1,0,0) + w_2 EXP \qquad (9)$$

$$c_{t+1} = 0.49(0.99y_t) + 0.51(0.98y_t + 0.02(I_{t-1} + b_{t-1}) + 0.18(I_t - I_{t-1}) + 0.82b_{t-1}) \qquad (10)$$

Table 5 demonstrates that the evaluation of model I.

The combination model Combines ANN, ARMA, and exponential smoothing based on the error weight of each model. Therefore, the mathematical Model II is as follows:

$$c_{t+1} = w_1 ANN + w_2 ARIMA(1,0,0) + w_3 EXP \qquad (11)$$

$$c_{t+1} = 0.34[t] + 0.32(0.99y_t) + 0.34(0.98y_t + 0.02(I_{t-1} + b_{t-1}) + 0.18(I_t - I_{t-1}) + 0.82b_{t-1}) \qquad (12)$$

Where:
t: output of ANN
Table 5 provides the results of the evaluation of this model.

Table 6. Fit statistics of two combination model

Criteria / Models	R^2	RMSE	MAPE
Model I	0.994	603.25	2.63
Model II	0.995	467.09	2.59

As Table 5 shows, there is a significant difference between the two models. The combination model that includes artificial neural network models enables error minimization.
The author found that Modern models (ANN) have improved error results, which is in good agreement with the results of the present study. The finding provides evidence of the Efficiency of the results of traditional and modern models.
Table 6 demonstrates the prediction values for the next 25 days.

Table 7. Forecasting values

Period	Forecast
02/27/21	48476.98
02/28/21	48789.19
03/01/21	49101.41
03/02/21	49413.62
03/03/21	49725.83
03/04/21	50038.04
03/05/21	50350.25
03/06/21	50662.47
03/07/21	50974.68
03/08/21	51286.89
03/09/21	51599.1
03/10/21	51911.32
03/11/21	52223.53
03/12/21	52535.74
03/13/21	52847.95
03/14/21	53160.17
03/15/21	53472.38
03/16/21	53784.59
03/17/21	54096.8
03/18/21	54409.02
03/19/21	54721.23
03/20/21	55033.44
03/21/21	55345.65
03/22/21	55657.86
03/23/21	55970.08

4. Conclusion

Important conclusions drawn from this work include:

1. These findings suggest that in general All traditional and modern methods are competitive and have proven to be efficient.
2. The relevance of the combination model is supported by the current findings.
3. The results of this study indicate that artificial neural network models minimize error and improve the results of the model compound.
4. The results of this investigation show that residual behavior is white noise.
5. The results of the present study also suggest that the combination model with ANN best the combination model without ANN.
6. The results presented here may facilitate improvements in the forecasting and adopt a model of a robust forecasting model that replies to the many fluctuations that occur in the bitcoin time series.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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