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Forecasting Using Time Series Analysis Method in Crypto Currency Period 2015 – 2022

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Abstract:- Cryptocurrency is a digital currency that is currently much interested as an alternative investment. ARIMA, GARCH, and Holt's Winter method are one of the methods used for forecasting time series data. This research aims to create a model and predict the price of bitcoin. The data used is secondary data in the form of daily closing price data for Bitcoin, Ripple, and Litecoin, as much as 2,520 daily closing price data starting from August 07, 2015 to June 30, 2022, to predict Bitcoin, Ripple, and Litecoin prices for the following 30 periods starting on July 01, 2022 to July 31, 2022. This study determines the forecasting model with an error below 5% with MSE, MAPE, and U Theil. The study results indicate that the Holt Winter forecasting model is suitable for Bitcoin, Ripple, and Litecoin. The Holt Winter Bitcoin model produces a MAPE value = 2.605%, Holt's Winter Ripple produces a MAPE value = 4.334%, and Holt's Winter Litecoin produces a MAPE value = 3.598%.

Keywords:- *Cryptocurrency, Forecasting, ARIMA, GARCH, Holt Winter.*

I. INTRODUCTION

Cryptocurrency is a financial breakthrough using cryptographic technology to transmit data and process digital currency exchanges securely. Cryptocurrencies have several advantages and disadvantages. The advantages of cryptocurrency with blockchain technology are a decentralized system without central banking intervention, freedom and speed in the transaction process, and identity security. Meanwhile, the weakness of cryptocurrencies is that it has fluctuating price volatility with high risk, there are no underlying assets, and there is the possibility of being a means of crime. In addition, cryptocurrencies such as Bitcoin, Ethereum, Tether, and others are trading commodities with high volatility where the price of these digital assets rises and falls very quickly. Hence, it is hazardous to be used as an investment/trading alternative.

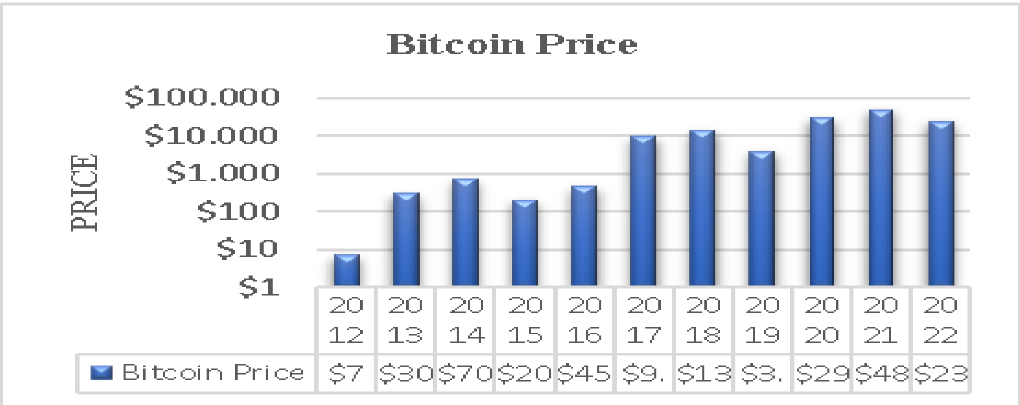

Fig. 1: Graph of Bitcoin Price

Bitcoin price fluctuates from year to year. In 2013, the price of Bitcoin experienced two bubble prices, namely a very high price spike accompanied by a decrease in price which occurred in a short time. The first Bubble Prices occurred in April 2013 when the Bitcoin price was $220, after which it dropped to $70 within two weeks. The second price movement occurred in December 2013; the price of Bitcoin rose sharply and touched the figure of $ 1,156. Bitcoin declined to its lowest level of $315 in early 2015. After going through a long price decline, the price of Bitcoin surged to $20,089 in December 2017. However, Bitcoin again experienced a price decline in 2018 to $3857. From December 2020 to January 2021, the price increase reached 224%. As of March 2021, Bitcoin hit a new high of around $60,000. At its peak, Bitcoin reached its highest

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price level (All-Time-High) at $64,804 in April 2021. (BAPPEBTI, 2021).

There is a problem that is full of uncertainties in the price of cryptocurrencies, which are volatile and quite liquid. Moreover, there is a change in the behavior of Indonesian people who save their money in cryptocurrency. So there is a lot of demand and supply with the size of the market and the availability of coins/tokens supply in Indonesia. Therefore, forecasting analysis with the best validity is needed so crypto asset investors can invest safely. Forecasting is needed as an instrument in making decisions to deal with future events.

II. LITERATURE REVIEW

A. *Forecasting*

Forecasting is about predicting the future as accurately as possible given all available information, including historical data and knowledge of future events that might impact the forecast. The ultimate goal of forecasting is to determine what companies/individuals should do in the future in order to achieve the expected goals (Rob J Hyndman and George Athanasopoulos, 2018). According to Heizer, et. al (2017) based on the time horizon, forecasting is grouped into three parts, namely long-term, medium-term and short-term forecasting.

B. *Time Series*

The quantitative model consists of a time series analysis forecasting model and a causal model. Time series forecasting models use historical data to predict the future assuming a pattern of data in the past that continues into the future (Fanji, et al, 2021). In other words, a time series is used to see what has happened over a certain period and a series of past data to make predictions (Heizer & Render, 2017). The primary purpose of using time series analysis is to obtain and see the relationship between Yt and Yt−1,Yt−2, …where Yt is an observation Y at time t and Yt−1,Yt−2, … is an observation Y at time-t. The previous time (t 1, t 2, and so on) (Asrirawan et. al, 2022).

C. *ARIMA*

According to Suliyanto (2008), the ARIMA method only uses one variable as the basis for making projections, so in this model, no independent variables are used to predict the dependent variable. The ARIMA model is a combination of the Autoregressive (AR) model and the Moving Average (MA) model so that in this model, the independent variable is the previous value of the dependent variable (lag), and the residual value of the previous period. The general form of this model is:

$$Y_t = \alpha + b_1 Y_{t-1} + \cdots + b_n Y_{t-n} - m_1 e_{t-1} - \cdots - m_n e_{t-n} + e_t$$

D. *GARCH*

The GARCH model was carried out to avoid large ARCH orders and provide more practical results than the ARCH model. According to Nachrowi & Hardius (2006) on the GARCH model, the residual variance (σ_t^2) is not only influenced by the residuals of the previous period (u_(t-j)^2) but also the residual variance of the last period (σ_(t-1)^2). The general form of this model is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$$

E. *Holt-Winters*

The Holt-Winters model is a technique for predicting the characteristics of time series data. The Holt-Winters model is a popular forecast for time series data. According to Hyndman et al. (2008), the Holt-Winters method is based on three smoothing equations: level, trend, and seasonality. The general form of this model is:

Level formula
ℓBt = ?(PBt − SBt − m) + (1 − ?)(Lt − 1 + bt − 1)
Trend formula
bBt = ?(ℓBt − ℓBt−1) + (1 −)bBt−1 ?
Seasonal formula
SBt = (PBt − ℓBt – 1 − bBt − 1) + (1 −) SBt – m
Forecasting formula
FBt+m = ℓBt + bBtm + SBt − s + m

F. *Evaluation of Forecasting Models*

A suitable projection method is a projection method that gives the lowest error rate. The error rate is the difference between the actual and projected values (Suliyanto, 2008).

a) Mean Absolute Percentage Error (MAPE)
Mean Absolute Percentage Error (MAPE) is a technique to find the average value of absolute percentage error. Mean Absolute Percentage Error (MAPE) is a measure of relative accuracy used to determine the percentage deviation of forecasting results (Suliyanto, 2008).

$$MAPE = \frac{\dfrac{\sum_{t=1}^{n} |Y_t - \hat{Y}_t|}{Y_t}}{n}$$

b) Mean Square Error (MSE)
Mean Square Error (MSE) technique to find the average value of the squared error. Mean Square Error (MSE) is calculated by adding the squares of all forecasting errors in each period and dividing them by the number of forecasting periods (Suliyanto, 2008).

$$MSE = \frac{\sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2}{n}$$

c) U-Theil
The U-Theil coefficient is one measure of the forecast model's accuracy that compares the actual data with the forecasted data that can overcome the small number of forecasts (Petris, 2010).

$$U\,Theil = \sqrt{\frac{\sum_{i=1}^{n+1} \left(\dfrac{\hat{y}_{i+1} - y_{i+1}}{y_i}\right)^2}{\sum_{i=1}^{n+1} \left(\dfrac{\hat{y}_{i+1} - y_1}{y_i}\right)^2}}$$

III. RESEARCH METHODOLOGY

A. *Type and Source of Data*

The method used in this research is the quantitative causality statistical inferential method. The type of data used in this study is time series data which is secondary data. The data used in completing this research is data from the daily closing price of crypto assets, namely the price of crypto assets during 2015 - 2022. The process of collecting data used in this study is using documentation. The data source is obtained from www.coinmarketcap.com.

B. *Population and Sample*

The population in this study is all daily closing price data for cryptocurrencies from August 7, 2015, to June 30, 2022, totaling 2,520 daily closing price data for Bitcoin, Ethereum, and Tether. In this study, the sampling technique used is non-probability sampling, with the technique taken is saturated sampling (census). According to Sugiyono (2019), the saturated sampling technique is a sampling technique when all members of the population are used as samples. Therefore, the authors chose a sample using a saturated sampling technique because the population is relatively small, so the sample used in this study amounted to 2,520 daily closing price data.

C. *Technique and Analysis of Data*

The method of analyzing the data used in the completion of this study uses multiple regression analysis. The purpose of the data analysis method in this study is the extent to which it analyzes the forecasting model for Cryptocurrency prices. Analysis data in this study were processed using EVIEWS 8.

IV. DISCUSSION AND RESULS OF RESEARCH

A. *ARIMA*

a) Identification of Model

The first step that needs to be done in forecasting using ARIMA is to identify the model using the ADF test. ADF test to determine whether the data is stationary or not. If the ADF test results show Prob < 0,05, then the data is stationary, and vice versa. On the other hand, the data is not stationary if the ADF test results show Prob. > 0,05.

Based on the results of the static test data using the ADF Test at the level, it was obtained that Ripple (XRP) had a significant value with a prob value of 0,0031. Therefore, the value of d on Ripple is 0. Data that is not stationary at the level is performed first difference.

Code	Root Test	Prob.	Information
BTC	1st Difference	0,0001	Stasioner
XRP	Level	0,0031	Stasioner
LTC	1st Difference	0.0000	Stasioner

Table 1: Result Adf Test

Non-stationary cryptocurrency data at the level is then carried out—the ADF Test returns at the first difference level. The results of this test show that the data is stationary because the prob value is < 0,05. For stationary company data at the rst difference level, the value of d = 1.

b) Parameter Estimation of ARIMA Models

Akaike Information Criterion and Schwarz Criterion are criteria used in determining the best ARIMA model. Therefore, the best ARIMA model is the model that has the minor AIC criterion and Schwarz criterion values. To determine the ARIMA model estimation assisted using the program Eviews 8.

Nama	ARIMA Model	AIC	Schwarz Criterion	Information
BTC	ARIMA (9,1,9)	16,338	16,347	
	ARIMA (9,1,12)	16,336	16,345	
	ARIMA (12,1,12)	16,336	16,346	
	ARIMA (12,1,9)	16,335	16,345	Best Model
XRP	ARIMA (1,0,1)	-3,193	-3,184	
	ARIMA (0,0,1)	-0,292	-0,285	
	ARIMA (1,0,0)	-3,193	-3,186	
	ARIMA (2,0,1)	-3,195	-3,186	Best Model
	ARIMA (2,0,0)	-2,481	-2,474	
LTC	ARIMA (6,1,6)	6,752	6,761	
	ARIMA (10,1,6)	6,750	6,759	Best Model
	ARIMA (10,1,10)	6,763	6,772	
	ARIMA (6,1,10)	6,753	6,762	

Table 2:. Arima's Best Model Estimation

c) Diagnostic Checking

A heteroscedasticity test needs to be done to prove the adequacy of the ARIMA model. The heteroscedasticity test used in this study is the white test. The prob. f value < 0,05 means the model contains heteroscedasticity, and the prob. f value > 0,05 means the model contains homoscedasticity.

Code	Estimation Model	Prob. f	Information
BTC	ARIMA (12,1,9)	0.0000	Heteroscedasticity
XRP	ARIMA (2,0,1)	0.0000	Heteroscedasticity
LTC	ARIMA (10,1,6)	0.0000	Heteroscedasticity

Table 3: Diagnostic Test

Based on the results shown in the table, it is obtained that the ARIMA model contains heteroscedasticity, so the ARIMA models are models that have an error variance that is not constant. Prob F value of the three cryptocurrencies with a value of 0,0000.

B. GARCH

a) Parameter Estimation of GARCH Models
Akaike Information Criterion and Schwarz Criterion are criteria for determining the best GARCH model. The best GARCH model is the model that has the most minor AIC Criterion and Schwarz Criterion values. To determine the best GARCH model, it is assisted by the program Eviews 8.

Code	Model GARCH	Akaike Criterion	*Schwarz Criterion*
BTC	GARCH (1,1)	16,29351	16,30746
XRP	GARCH (1,1)	0,445444	0,459339
LTC	GARCH (1,1)	10,02250	10,02250

Table 4: Garch's Best Model Estimation

b) Diagnostic Checking
A heteroscedasticity test needs to be done to prove the adequacy of the GARCH model. The heteroscedasticity test used is the white test. The prob. f value < 0,05 means the model contains heteroscedasticity, and the prob. f value > 0,05 means the model contains homoscedasticity.

Code	Estimation Model	Prob. f	Information
BTC	GARCH (1,1)	0.0000	Heteroscedasticity
XRP	GARCH (1,1)	0.0000	Heteroscedasticity
LTC	GARCH (1,1)	0.0000	Heteroscedasticity

Table 5: Diagnostic Test

c) Holt-Winters
i. Parameter Estimation of Holt-Winters Models
There are three smoothing parameter values in Holt-Winter's method, namely alpha, beta, and gamma. Alpha (α) is the value of the smoothing level coefcient of the process. Beta ( ) is the value of the trend smoothing coefcient. Gamma (γ) is the value of the seasonal smoothing coefcient. The value of alpha, beta, and gamma is between 0 to 1. This research uses an additive model. The following is the smoothing parameter value from the model for 3 (three) cryptocurrencies obtained from the initial default value using the Eviews 8 software.

Code	Parameter		
	Alpha (α)	**Beta (β)**	**Gamma (γ)**
BTC	0,9700	0,0000	0,0000
XRP	0,8	0,0000	0,0000
LTC	0,9700	0,0000	0,0000

Table 6: The Parameter Analysis Results

ii. Comparative Analysis Evaluation of Accuracy
The evaluation comparison analysis stage displays the best model of each method with the most minor Mean Absolute Percentage Error. This stage compares the MAPE values between ARIMA, GARCH, and Holt-Winters to get the best model and is used for forecasting the cryptocurrency.

Code	MAPE (%)		
	ARIMA	**GARCH**	**Holt-Winter**
BTC	118,53	73,54	2,605
XRP	78,71	357,99	3,598
LTC	163,57	163,57	4,334

Table 7: The Parameter Analysis Results

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Based on the data above, looking at the MAPE value is to find the best forecasting model. The best forecasting method for Bitcoin, Ripple, and Litecoin is the Holt Winter method with BTC MAPE = 2.605%, XRP MAPE = 4.334%, and LTC MAPE = 3.598%.

iii. Forecasting

Based on the analysis of the evaluation of the MAPE value on the ARIMA model, GARCH and Holt-Winters. Holt-Winters can be used for the forecasting process. Forecasting data is the value generated for each case of the cryptocurrency. The following is Figure 2, which is the result of forecasting from August 7, 2015, to June 30, 2022.

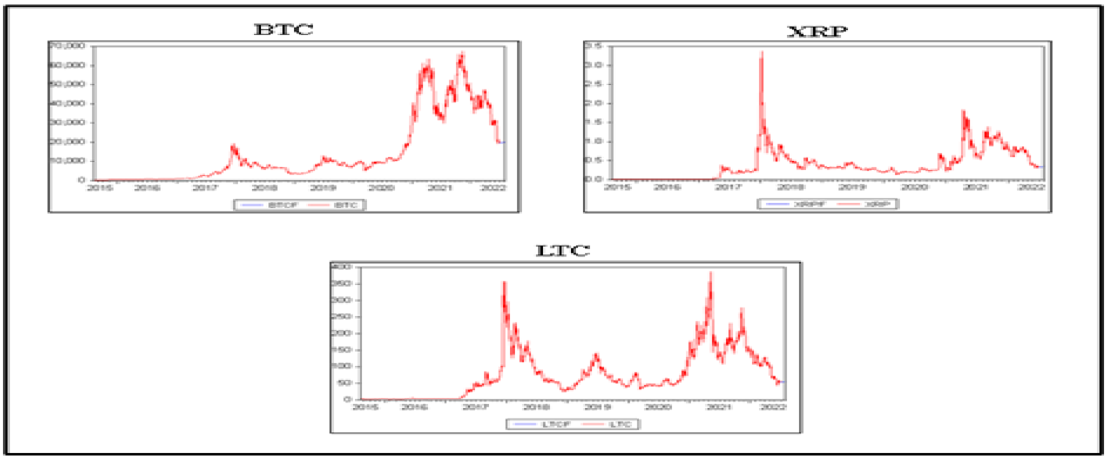

Fig. 2: Forecasting of Bitcoin Price, Ripple Price and Litecoin Price

Based on Figure 2 shows how the movement of BTC, XRP, and LTC forecast plots from the original data plot. The red line shows the actual BTC, XRP, and LTC price data, while the blue line shows the BTC, XRP, and LTC price forecasting data. It can be seen that the blue forecast line indicates that the pattern is similar to the pattern in the previous seasons, which experienced price stability in that period.

V. CONCLUSION

Based on the results and discussions carried out in this study, it can be concluded that:

- A good forecasting model must be able to predict changes in cryptocurrency prices that are uncertain or patterned, making it difficult to determine. Judging from the results of data accuracy that the price movements of Bitcoin, Ripple, and Litecoin can be predicted using the Holt-Winter model. Holt - Wintertime series model as a better Bitcoin, Ripple, and Litecoin forecasting model compared to ARIMA and GARCH with BTC MAPE = 2,605% accuracy, XRP MAPE = 4,334%, and LTC MAPE = 3,598%. It can be concluded that the price movements of Bitcoin, Ripple, and Litecoin are predictable because the price of cryptocurrency is formed due to the demand and supply of investors.
- Bitcoin cryptocurrency forecasting results are predicted to experience a price decline in July. Meanwhile, Ripple and Litecoin are predicted to experience price stability in July. It is known that the results of Bitcoin price forecasting in July 2022, with an average of $19.836,12, experienced a decrease from the previous month. It is known that Ripple's price forecast results in July 2022 with an average of $0,3353, which experienced price stability from the previous month. Litecoin in July 2022 with an average of $53,978992, which has increased in price from the previous month. It can be concluded that the Holt-Winter model can predict the future price of Bitcoin, Ripple, and Litecoin cryptocurrencies. Cryptocurrencies become predictable financial instruments so that investors can avoid losses.

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