RIK International Journal of Science and Technological Research (RIK-IJSTR) *Vol. 5 No. 5, September 2019*
ISSN: 2350-6310 (Print)
ISSN: 2350-543X (Online)

Forecasting Ripple Coin with a Seasonal ARIMA Model

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ABSTRACT

The cryptocurrency Ripple coin, from the crypto market was examined. The time chart shows a negative downward trend. Inventory price forecasts constantly attract warnings related to your direct monetary benefit plus the associated hardship. In this article, we carry out forecasting the price of Ripple coin using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The model was chosen for its great relevance. The parameters selected for the SARIMA model has been performed using the Akaike information criterion (AIC) and the corrected Akaike information criterion (AICc). The results and analysis with the R software shows that it gave an accuracy of 68.54%.

Keywords: SARIMA Model, AIC, Ripple Coin, Forecasting.

Introduction

The data observed over time give rise to temporary (temporal) series. The analysis of time series data makes it possible to understand the behavior of data over time. The purpose of time series analysis procedures is to identify trends, investigate possible cases, and often make predictions for the unknown time. The temporal information of a datum plays an important role in the pattern identification step. If a temporary reason is identified, the possible causes of the late reason will be examined. Then, the response variable can be modeled as a function of time or as a function of the direct cause of the forecast. The importance of time in a dataset is not limited to those cases in which we intend to do a time series analysis. Time is often an essential part of the research dataset. This is partly because it can often be adjusted for underlying variables and the effects of unmeasured or misunderstood factors. Time series data can be decomposed into trend, seasonality, cycle and random fluctuation components. The trend component of a time series is the long-term trend or the change in the average of the data. The existence of a trend in the data of a time series can be identified simply by comparing the averages of the data of a time series at different intervals or simply by means of a regression analysis of the data during the period. Time, in years, months, days or hours, is a device that links a phenomenon to a set of common and stable reference points. The concept of time series is essentially based on historical observations. This involves explaining past observations to try to predict, those of the future.

Seasonal ARIMA Models

A time series is said to be seasonal of order d if there is a tendency for the series to present behavior after each time interval d. Traditional time series methods involve identification, decryption and estimation of traditional components: secular trend, seasonal component, cyclical component and irregular movement. For forecasting purposes, they are reset. These kind of techniques can be quite tricky and sometime misleading.

The time series $\{X_t\}$is said to follow a multiplicative (p, d, q)x(P, D, Q)s seasonal ARIMA model if

$$A(L)\Phi(L^s)\nabla^d\nabla^D{}_sX_t = B(L)\Theta(B^s)\varepsilon_t \quad (1)$$

where Φ and Θ are polynomials of order P and Q respectively. That is,

$$\Phi(L^s) = 1+\phi_1L^s + . . . +\phi_p L^{sP} \quad (2)$$

$$\Theta(L^s) = 1+\theta_1L^s + . . . +\theta_q L^{sQ} \quad (3)$$

where ϕ_i and θ_j are constants such that the zeros in equations (2) and (3) are all outside unit circle for stationarity or inversion, respectively. Equation (2) represents the autoregressive function the operator while (3) represents the moving average operator.

The existence of a seasonal nature is usually evident on the weather chart. More for a season The ACF series or correlogram shows a peak in seasonal change. Box and Jenkins (1976) and Madsen (2008) are some of the authors who have written extensively on these models. Knowledge of the theory the properties of the models provide the basis for their identification and estimation. The purpose of this the document consists of adapting a seasonal ARIMA model to the Ripple coin price (XRP).

Materials and Methods

The data for this work are the average weekly price rates of the Ripple Coin from 02/02/2015 to 21/10/2018, a total of 195 observations for weekly dataset and 13 weeks was reserved for testing the model, the data is available and accessible in the www. yahoo.com/finance website.

Determination of the Orders d, D, P, q and Q

A seasonal differentiation is needed to suppress the seasonal trend. If there is a secular non-seasonal trend differentiation will be necessary. To avoid excessive complexity of the model, it was reported that the the difference between d and D must add up to a maximum of 2 (that is, d + D <3). If the ACF of the differentiated series has a positive peak in seasonal change, so a seasonal AR component is suggestive; if it has a negative peak, then a seasonal term MA is suggestive As already mentioned above, an AR (p) model has a PACF that is truncated at change p and a MA (q) has an ACF that is truncated at offset q. In practice, $\pm 2 / \sqrt{n}$ where n is the sample size are the limits of non-significance for the two functions.

Model Estimation

The implication of the white noise process in an ARIMA model implies a non-linear iterative process in parameter estimation. An optimization criterion such as the minimum sum of squares of error, the maximum probability or entropy is used. Generally a first estimate is used. Each iteration is expected be an improvement on the latter until the estimate converges to an optimal estimate. However, for pure There are techniques for linear optimization of pure AR and MA models (see, for example, inset and Jenkins (1976), Oyetunji (1985)). There are attempts to adopt linear methods to estimate ARMA models (See, for example, Etuk (1987, 1998)). We will use the R software that uses least squares approach involving non-linear iterative techniques.

Diagnostic Checking

The model that fits the data should be tested for goodness of fit. We will do an analysis of the model residuals. If the model is correct, the residuals would not be correlated and would be they follow a normal distribution with zero mean and constant variance. The autocorrelations of the residuals must not be significantly different from zero.

Results and Discussion

Table 1

Descriptive statistics for Ripple

Statistics	Ripple
Mean	0.2764
Median	0.1085
Std. Error	0.0689
SD	0.4136
Kurtosis	7.5385
Skewness	2.4517
Minimum	0.0040
Maximum	1.9800

Note.

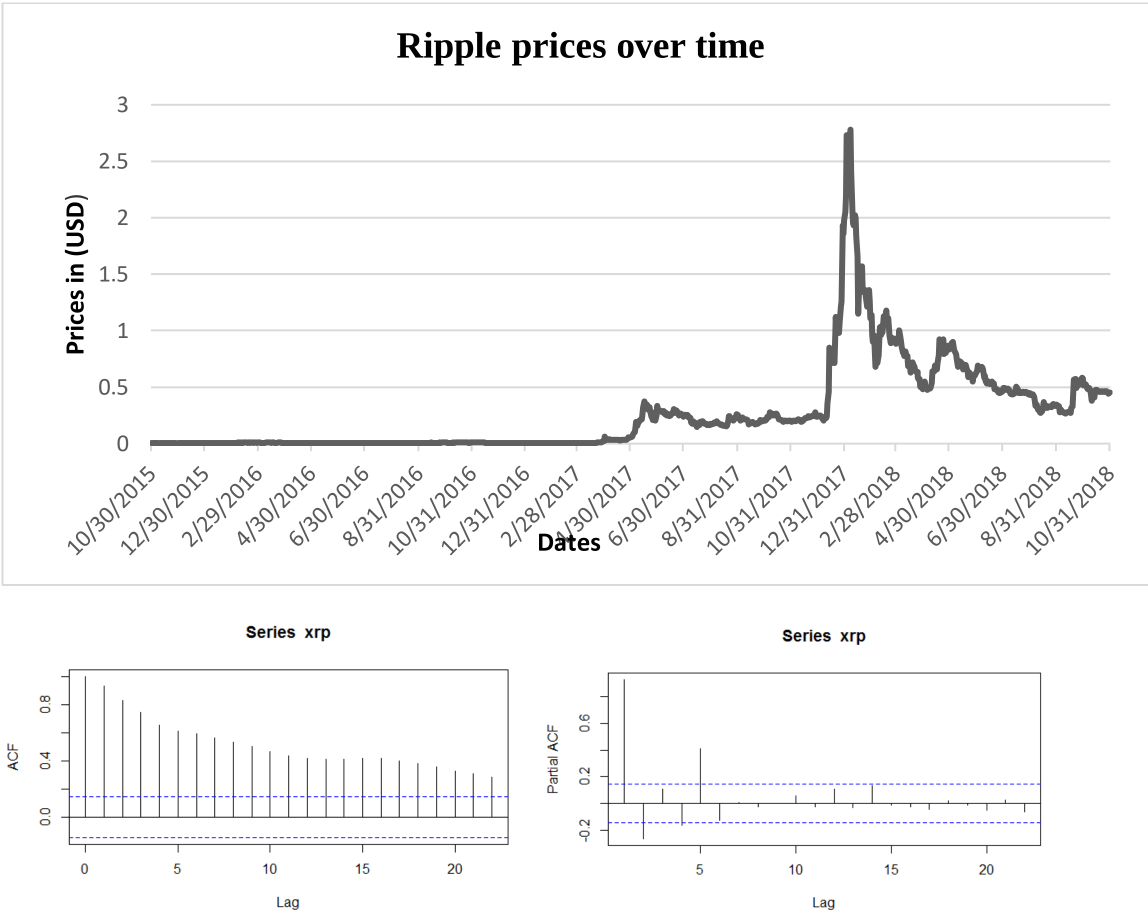

Figure 1. Time plot, ACF and PACF of weekly Ripple Coin

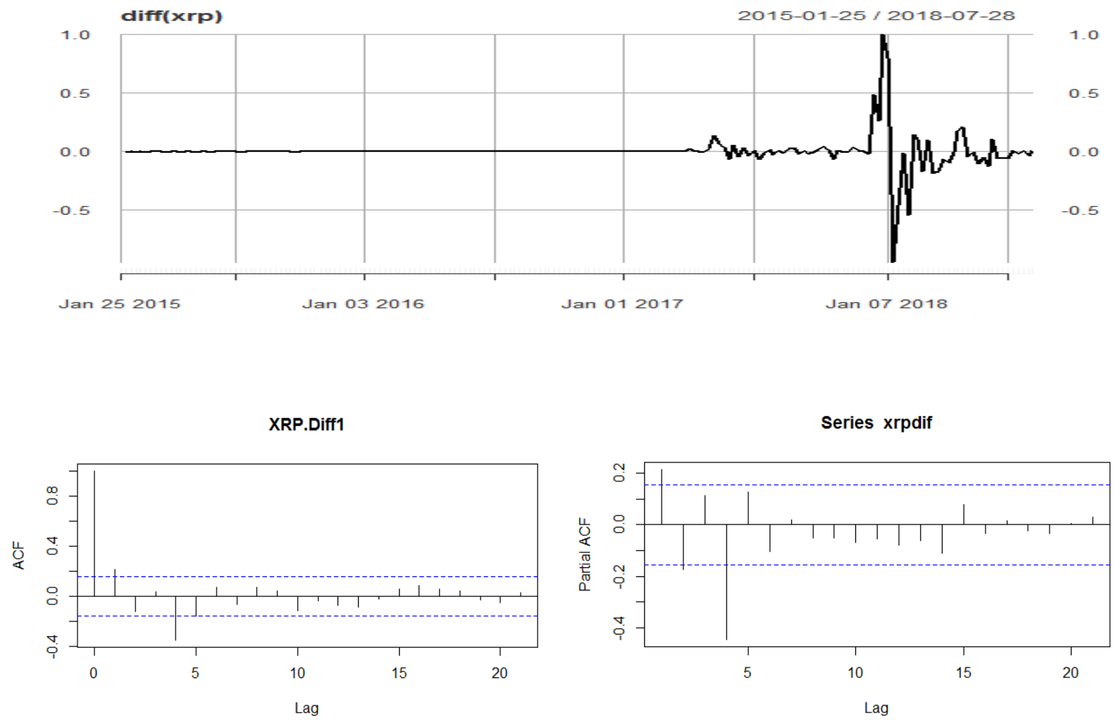

Figure 2. Showing the first difference, ACF and PACF for Ripple Coin

By looking at the ACF and PACF of the first difference for the Ripple coin time series, we can say that it has become stationary, so we only need to differentiate the data once d = 1. The root tests were performed units (KPSS) and (ADF) for the first differentiation of Ripple time series and the results of both tests are shown in Table 2.

Table 2

P-values of (KPSS) and (ADF) tests of the first difference for Ripple Coin

Test	P-Values
ADF	0.01
KPSS	0.1

From table 2, the p-value of the test (KPSS) is 0.1, which is greater than 0.05, and the p-value of (ADF) the test is 0.01, which is less than 0.05. This result indicates that the weekly time series of Ripple coin is stationary. Therefore, no additional differentiation is necessary.

Model Selection

The strategy used to select the appropriate model from the competing models is based on the Akaike Information Criteria (AIC) and Akaike Corrected Information Criteria (AICc). The R software is used for trial and error to determine the best fit model. We will examine the three SARIMA models, as well as some variations, and calculate their AIC, AICc and their values. Table 3 gives the suggested models with their respective adjustment statistics.

Table 3

The values of (AIC, AICc) for suggested SARIMA models for Ripple Coin

ARIMA Model	AIC	AICc
ARIMA(2,0,2)(1,0,0)7	-141.58	-140.52
ARIMA(1,0,0)(1,0,0)7	-115.55	-115.26
ARIMA(0,0,1)(0,0,1)7	-16.56	-16.27
ARIMA(2,0,2)(0,0,1)7	-143.47	-142.65
ARIMA(2,0,4)(1,0,0)7	-145.58	-145.27
ARIMA(2,0,4)(0,0,1)7	-145.57	-144.27
ARIMA(2,0,4)(1,0,1)7	-145.29	-144.69
ARIMA(3,0,4)(1,0,0)7	-154.37	-153.72
ARIMA(3,0,4)(1,0,1)7	-151.45	-151.23
ARIMA(3,0,4)(2,0,1)7	-150.42	-149.68

Model Estimation

SARIMA (3, 0, 4)(1, 0, 0)7 Model for Ripple Coin

By using R software packages to estimate the parameters of the best model SARIMA (3, 0, 4) (1, 0, 0)$_7$ we have the results:

Coefficients:

ar1	ar2	ma1	ma2	ma3	ma4	sar1	sma1
-0.2716	0.1489	0.5871	1.6809	0.7936	0.2859	0.1627	0.2520

and using the equation 3.30 the fitted model in this case is

$(1+0.2716B-0.1489B^2)(1-0.1627B^7)(1-B^7)\,\hat{X}_t$ = $(1-0.5871B-1.6809B^2-0.7936B^3-0.2859B^4)$

$(1-.2520B^7)\hat{\varepsilon}_t$...(4.1)

with estimated variance, $\hat{\sigma}^2 t$ = 0.01831 and log likelihood = 87.18.

Diagnostic Checking

In time series modeling, the selection of the model that best fits the data is directly related to the adequate performance of the residual analysis. The residuals of the adjusted model SARIMA (2, 0, 2) (0, 0, 0) 7 that was selected in Table 5 are shown in Figure 3, this is a graph of the normalized residuals, l 'Sample ACF of residuals , normal QQ plot and p-values for the Ljung-Box test statistic for the entire range of k-values from 9 to 36. The 5% horizontal dotted line helps to judge the size of the p-values. All peaks matter. The standard residuals QQ plot that explores the shape of the distribution suggests that the distribution may have a thicker tail than a normal distribution and may be somewhat skewed to the right and show some non-normality in the tails of the distribution and a nearly straight line suggesting that the residuals roughly follow the normal distribution, and the pattern appears to match.

Forecasting SARIMA Model

One of the main objectives of this study, and of time series analysis in general, is to use the built model to calculate forecasts. The ARIMA models provide good estimates of the series before its realization. The purpose of in-sample prediction is to test the predictability of the model. If the magnitude of the difference between the predicted and actual values is small, the model has good predictive power. In our case, SARIMA showed good results as shown in Table 4.

Table 4

Forecasting results for SARIMA (3,0,4)(1,0,0)7 of Ripple Coin

Weeks	Actual Coin Price	Forecast Price
1	0.4347	0.4354
2	0.2958	0.4142
3	0.3414	0.3858
4	0.3230	0.3723
5	0.3417	0.3496
6	0.2759	0.3370
7	0.2810	0.3293
8	0.5713	0.3152
9	0.5717	0.3071
10	0.4820	0.2988
11	0.4064	0.2886
12	0.4613	0.2838
13	0.4620	0.2787

Model Accuracy

Because of the fundamental importance of time series forecasts in many practical situations, care must be taken in selecting a particular model, in estimating the accuracy of forecasts, and in comparing different models. To compare the forecasting performance of different models, there are many statistical measures that can be used for this purpose. The most widely reported "forecast performance measures" are shown in the table 5.

Table 5			
SARIMA Model Accuracy Check			
MSE	RMSE	MAE	MAPE
0.023211	0.152351	0.1347	31.45368

From Table 5, the precision of the model is 68.54%, because the mean absolute percentage error (MAPE) is 31.45368, so our accuracy of the model is 100% - 31.4536 = 68.54%.

Conclusion

This study highlighted the SARIMA model for predicting Ripple coin price in the short term. After collecting enough real data to create stock market data, the SARIMA model is implemented in the dataset used to improve the short term provide. The application of the model in the case of bank transaction data allowed verifying its accuracy and demonstrating your presentation skills. About 195 observations were collected to implement their predictions and The best SARIMA model was selected based on the best known criteria, AIC, another important observation is that the predictive accuracy of the SARIMA model is 68.54% and gradually decreases at this stage of the growth process from one period to another. This model can be applied and is suitable for high-tech market cases, especially banks, such as provides a meaningful indicator for the future. The method was limited to a short-term prognosis and is not useful in Long-term. Future research on this topic includes other forward-looking market data, such as industry data and any data that it is measured in time. When applied to real data to exchange with, the information about the results must be taken into account, as it plays an important role in the price actions of most of the world's coins.

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