

Time Series Modelling and Forecasting for Computer Forms (Malaysia) Bhd, in Bursa Malaysia

Loshana Parthipan¹ Kamil Khalid²

^{1,2}Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology,
Universiti Tun Hussein Onn Malaysia, Pagoh Edu Hub, 84600, Johor, MALAYSIA

*Corresponding Author Designation

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Abstract: In this study, we examine the stock price predicting of Computer Forms (Malaysia) Bhd from 2016 to 2021 and select the best model. Visualizing a time series requires a lot of apparent statistical data collected at regular intervals. The use of autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedasticity (GARCH) models rather than determining directly produces more legitimate and solid results. There are three ARIMA models: (0,1,1), (1,1,0) and (2,1,0). The best model (0,1,1) has the lowest MSE and the highest Ljung-Box p-value. Comparing the GARCH (1,1) models, the normal gaussian/distribution GARCH (1,1) model is picked as the best. MAE, RMSE, and MAPE are used to assess forecasting accuracy. It was concluded the GARCH model is the best way to forecast Computer Forms Bhd, Bursa Malaysia.

Keywords: Forecasting, ARIMA, GARCH

1. Introduction

The stock market has historically been a crucial component of a country's economy throughout this period of globalization. Financial interchange is critical to the development of the government's business and commerce, which eventually affects the country's economy as a whole. That is why the government, business, and, unexpectedly, the nation's national banks all keep a close eye on the financial exchange's activities.

The Computer Forms (Malaysia) Bhd [1] incorporates general personal computer structures, such as receipts and bills of replenishment, stock structures, such as three-line and simple structures, security structures, such as bank checks and voucher coupons, optical imprint acknowledgment or optical character acknowledgment (OMR/OCR) structures, and mail/pressure seal mailers, such as pay envelopes and answer envelopes. From 2016 to 2021 [2], the Company, through its subsidiaries, is engaged in the arrangement of information or data executives, advanced printing, wrapping or fixing

*Corresponding author: kamil@uthm.edu.my

structures, and mailing administrations, as well as the printing and provision of activity books and magazines, as well as the printing and provision of adaptable packaging.

Our country's economy is in dire need of a boost, and investing in stock markets can help us achieve that. Investors should study about investment and forecast the future. Putting resources into an organization may not be a challenge for those who have worked in this industry. But it is also one of the ways they get temporary profit. Stock prices are not manufactured values. Forecasting demand enables companies to make more informed decisions about how much to produce and, as a result, prepare for raw material supply and inventory management [3]. However, plotting a time series requires a lot of apparent statistical data acquired over time. Changing the time series using autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedasticity (GARCH) model is preferred algorithmic methodology over determining directly, as it gives more legitimate and solid outcomes.

A source of knowledge and the profit of investing in stock market should be known by many people. It is very important for people to understand the type of forecasts method and how to invest in a proper and trustable stock value before investing. This way, many people starting from teenagers to old people can earn an income and also alternately help our Malaysian economy.

The objectives of this research are to build ARIMA and GARCH model to model time series, to compare between ARIMA and GARCH using accuracy measures and to forecast the best model for Computer Forms Bhd, Bursa Malaysia.

2. Methodology

From 2016 to 2021 [2], we are primarily interested in estimating the stock price of the company Computer Forms (Malaysia) Bhd, as well as determining the most acceptable model to use. The information used in this investigation was obtained from the website (<https://www.investing.com>). In this study, weekly data in the form of forecasting profit, monetary record estimates, or deals estimates for a 7-day time frame. The ARIMA and GARCH models are both used in this study to forecast as well as to understand which model is the most effective.

2.1 Auto Regressive Integrated Moving Average (ARIMA)

The Auto Regressive Integrated Moving Average (ARIMA) is certainly a class of models that clears out a given time series based on its own historical qualities, including lags and lagged predictor errors, and may be used to forecast future qualities. Some processes will be carried out in order to forecast the stock price. As a result, we must plot the data to determine the trend and pattern. ARIMA (p, d, q), where p denotes the AR order, d the degree of differencing, and q the MA order. This is how the model is written [4]:

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)(1 - B)^d y_t = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) e_t \quad Eq.1$$

In this model, y_t alludes to the i^{th} perception in the series of data, B alludes to the backshift operator ($B^j y_t = y_{t-j}$). ϕ 's indicates the non-occasional autoregressive boundaries, θ 's indicates the non-occasional moving normal boundaries, e_t alludes to a grouping of error factors with mean, 0 and variance, σ^2 .

By performing a Box-Cox transformation on the data in order to determine its stationarity. The transformation parameter is the autocorrelation function (ACF) or the partial autocorrelations function (PACF). Researches can potentially adjust a change to be as persuasive as possible in bringing a variable toward normalcy, regardless of whether it is contrarily or plainly skewed [5].

This data does not have a seasonal pattern, hence regular differencing must be used. While seasonal differencing must be used when there is a seasonal trend, it must be done with caution. The equations for seasonal and regular differencing are listed below [6].

Seasonal differencing :

$$y'_t = y_t - y_{t-12} \tag{Eq.2}$$

Regular differencing :

$$y'_t = y_t - y_{t-1} \tag{Eq.3}$$

The parameter of the ARIMA model is then estimated. If the *p-value* of the parameter being evaluated is less than 0.05, the calculated parameter is significant. A test of the model's suitability is required. The Box-Ljung test is a tool that will be used to evaluate the model.

H_0 : The model does not display absence of fit (the model is sufficient)

H_1 : The model show absence of fit (the model is deficient)

If the *p-value* is more than 0.05, the H_0 , hypothesis is rejected because the model is insufficient or inadequate. The optimal model has the highest *p-value* of the Box-Ljung test and the lowest *p-value* estimated parameter [7].

2.2 Generalized Autoregressive Conditional Heteroscedasticity

Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) is a summed-up type of ARCH. The GARCH model is best used for forecasting time series in financial markets with non-constant variance and volatility clustering [8]. This model is worked to avoid from the request for ARCH model which is as well high. GARCH model not just notices the relationship among a few residuals, yet in addition relies upon some past residuals. The ARCH model is straightforward, it confines the model for the contingent fluctuation (or identically) to follow an AR measure and consequently it might require more parameters to satisfactorily address the restrictive difference measure in examination with other more summed up models. Bollerslev expands Engle's unique work by permitting the restrictive fluctuation to follow an ARMA interaction [9]. This model is known as a summed up ARCH model, or GARCH model. When p and $q = 1$, GARCH (r, m) model can be composed as:

$$a_t = \sigma_t \varepsilon_t$$

Eq.4
Eq.5
Eq.6

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 \dots + \alpha_m a_{m-1}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_r \sigma_{t-r}^2$$

$$y_t = \mu + \phi y_{t-1} + \varepsilon_t$$

To appraise a , α and β , the standard technique for semi maximum likelihood estimation is utilized. This assessment technique utilizes powerful standard errors for inference. Given a large sample size, the powerful standard errors create great evaluations of the standard errors.[9]. The ARCH and GARCH models are symmetric in the sense that negative and positive shocks have similar effects on instability, which means that indicators of advancements or shocks have no effect on contingent instability, since squared developments reach the restrictive change condition [10].

Student t 's distributions are capable of coping with more severe leptokurtosis; it is defined as: [11]

$$\psi_\nu = \ln \left[((\nu - 2)\pi)^{-1/2} \Gamma\left(\frac{\nu}{2}\right)^{-1} \Gamma\left(\frac{\nu + 1}{2}\right) \right] \tag{Eq.7}$$

$\Gamma(\cdot)$ denotes the gamma distribution and ν is the degrees of freedom.

Generalized error distribution is defined as: [11]

$$\phi_\nu = (1 + \nu^{-1})\ln(2) + \ln(\Gamma(1/\nu)) + \ln(\lambda/\nu) \tag{Eq.8}$$

The initial definition of the GARCH model is based on a normal distribution for the disturbances, which is incompatible with the fat-tailed features that are often seen in time series data. As a consequence, the resultant estimations are inefficient. Traditionally, this issue has been solved using the student's t -distribution and the General Error Distribution (GED). Modelling and forecasting were conducted using Gaussian, Student t 's, and GED distribution densities in order to determine the most appropriate distribution for studying stylized facts regarding return volatility [12].

2.3 Equations

However, our study uses three accuracy metrics to analyze the deciding execution of ARIMA and GARCH models: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The best model is picked for the accuracy measures with the least worth which gives higher precision [13].

$$MAE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|}{n} \tag{Eq.9}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{n}} \tag{Eq.10}$$

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} \times 100 \tag{Eq.11}$$

MAE, MAPE and RMSE for various techniques are determined to look at the estimate exactness for all the strategy so it is simpler to choose the most suitable forecast technique among every one of the strategies [14].

3. Results and Discussion

3.1 ARIMA

A time series plot is used to examine changes across time. It also helps us collect data and understand results quickly. Time series graphic is also used to identify patterns, seasonality, and cyclical nature in data.

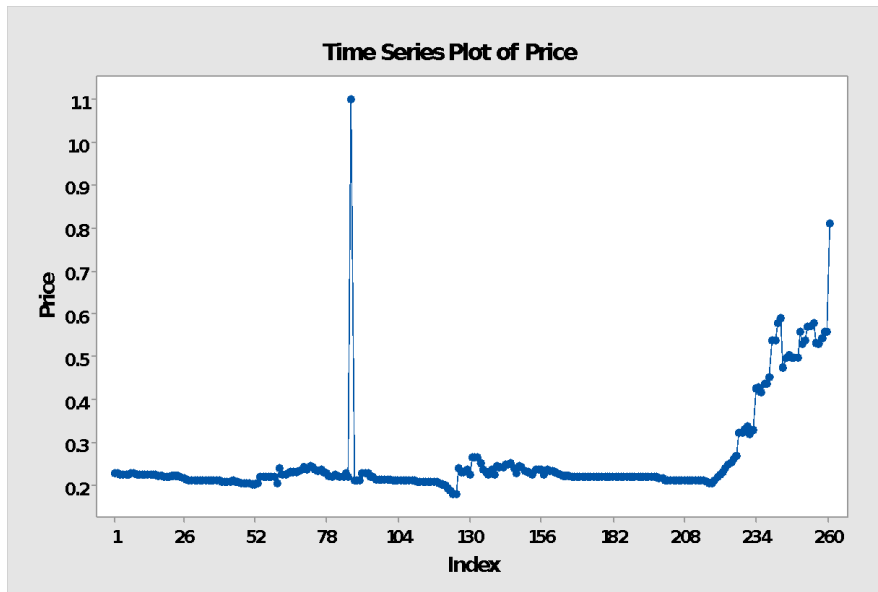


Figure 4.1: Time series plot of weekly closing price (2016- 2021)

Outliers can skew the outcomes of statistical analyses. They can result in parameter estimation biases, erroneous conclusions, and inaccurate volatility projections in financial data, among other things. As a result, when modelling financial data, it is necessary to include the detection and correction of inaccuracies. Outliers commonly skew time series data as a result of the data being influenced by uncommon and non-repetitive occurrences. Forecast accuracy is significantly reduced in such settings due to the carry-over effect of outliers on the point forecast and a bias in parameter estimation [15].

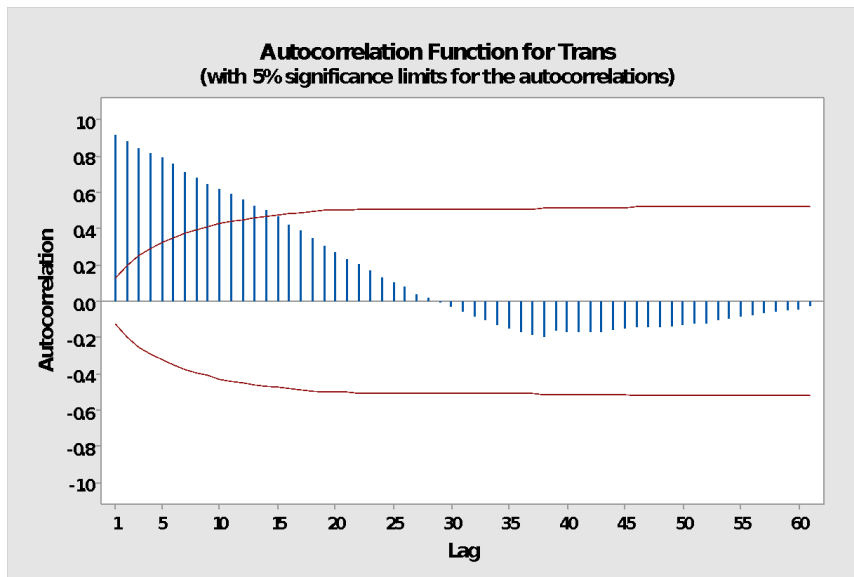


Figure 4.2: Autocorrelation function for Transformed data

Figure 4.2 shows that the data values are not stationary it is necessary to differentiate them. The data have 14 delays removed from the confidence interval, a large spike at the start and a slow drop. Figures 4.3 and 4.4 are the basis of model ARIMA (p, d, q). The autocorrelation function has three lags that are out of the significant limit, two lags that are out of the significant limit of the partial autocorrelation function and one differencing.

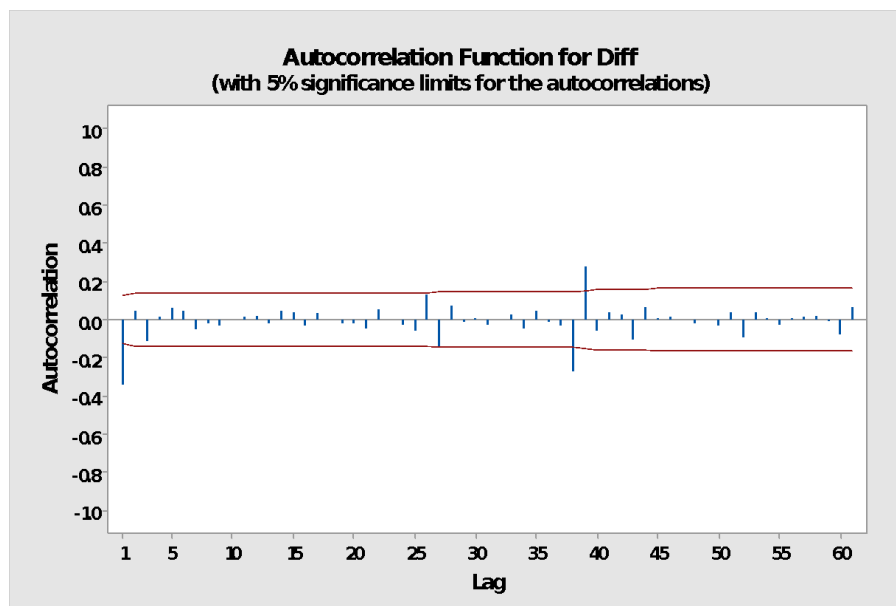


Figure 4.3: Autocorrelation function for 1st Differenced data

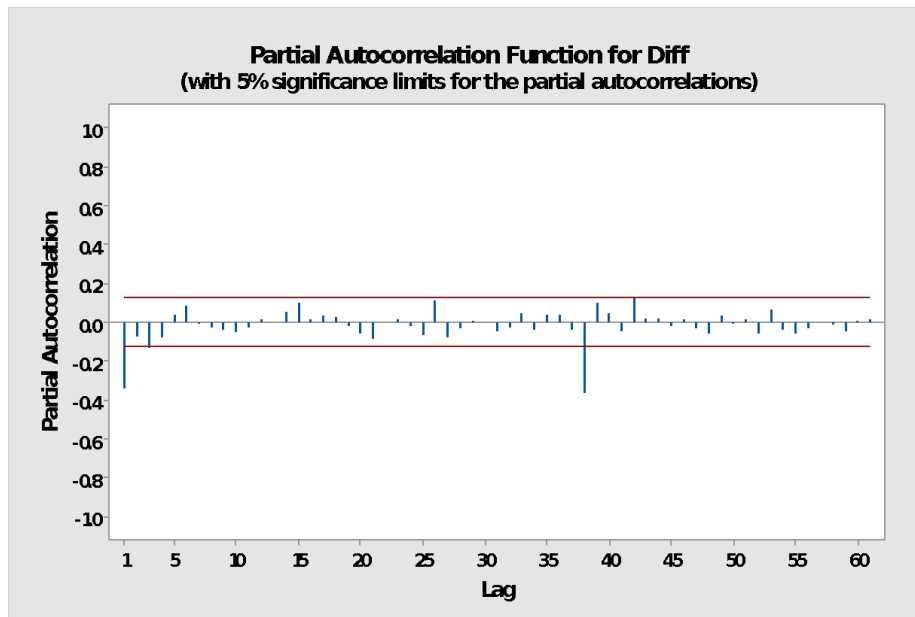


Figure 4.4: Partial Autocorrelation function for 1st Differenced data

3.2 Choosing the best ARIMA model

The p -values for Ljung-Box are more than 0.05 for model ARIMA (0, 1, 1) are 0.998, 1.000, 1.000 and 1.000 which implies all the residuals of the model are independent and that the model fits the assumption. Only three p -values for Ljung-Box are greater than 0.05 for model ARIMA (1, 1, 0) and ARIMA (2, 1, 0) are 0.098, 0.605, 0.931 and 0.459, 0.940, 0.997 respectively, implying that the residuals of the model are still independent and that the model fits the assumption. Even though it is statistically significant to select the most appropriate model we will be evaluating the mean square.

Besides that, the mean square are used to compare and contrast various models. The mean squares of the three models (0,1,1), (1,1,0), and (2,1,0) are 0.004006, 0.00495, and 0.00449, respectively, in this study. As a result, by comparing the mean squares of different models, it is determined that model ARIMA (0,1,1) has the lowest value and all of the residuals from the model are independent of one another, and the model fits the assumption, thus it is selected as the most appropriate model

3.3 GARCH

The GARCH (1,1) model shown in Table 4.13 is constructed with normal distribution, the constant variance term, ARCH, and GARCH parameters mostly have positive coefficients that are statistically significant at the 1% level.

Table 1: GARCH (1,1) diagnostics

	Normal Gaussian/Distribution	Student t 's	GED
Significant coefficients	0.0000	0.7711	0.0000
ARCH significant	0.0000	0.7768	0.2234
GARCH significant	0.9699	0.0000	0.0000
Log Likelihood	478.2605	1080.488	719.3743
Adjusted R-square	0.460453	0.459289	0.349649
SIC	-3.571991	-8.183124	-5.405325
Heteroscedasticity	No	No	No
Autocorrelation	No	No	No

According to Table 1, normal gaussian/distribution GARCH (1,1) model is the best model since it has a significant ARCH and coefficient value of 0.0000, it has the adjusted r-square of 0.460453. Whereas students t 's and GED both are rejected due to insignificant p -values.

3.4 Accuracy Measures

The accuracy measures are used to evaluate forecasting. However, in this research, three accuracy measures were employed to examine the deciding implementation of the ARIMA model and the GARCH model: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Based on Table 2 result, the GARCH approach has a superior predicting performance than the ARIMA modelling method.

Table 2: Accuracy measures values for ARIMA and GARCH model

ARIMA model		GARCH model	
MAE	0.061708	MAE	0.051734
MAPE	9.668025 %	MAPE	8.728517%
RMSE	0.094523	RMSE	0.066075

4. Conclusion

It was possible to use ARIMA modelling and GARCH method to look at the data values as the data had no trends or seasonal patterns in the data. Three ARIMA models are used in this study: (0,1,1), (1,1,0), and (2,1,0). The optimal model (0,1,1) is chosen because to its low mean square value and high Ljung-Box p -value. When GARCH (1,1) models are compared, normal distribution model is picked as the best model. MAE, RMSE, and MAPE are used as accuracy measures to evaluate predicting ability.

Thus, the ideal approach for forecasting the best model for Computer Forms Sdn Bhd, Bursa Malaysia from year 2016 to 2021, is the GARCH model.

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