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Predicting Closed Price Time Series Data Using ARIMA Model

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Abstract

Closed price forecasting plays a main rule in finance and economics which has encouraged the researchers to introduce a fit model in forecasting accuracy. The autoregressive integrated moving average (ARIMA) model has developed and implemented in many applications. Therefore, in this article the researchers utilize ARIMA model in predicting the closed time series data which have been collected from Amman Stock Exchange (ASE) from Jan. 2010 to Jan. 2018. As a result this article shows that the ARIMA model has significant results for short-term prediction. Therefore, these results will be helpful for the investments.

Keywords: short term forecasting, ARIMA model, closed Price time series

1. Introduction

Predicting remains a hot topic for researchers since the institutions are emphasis on two directions which are investment decision making and developing an effective strategy about their future work. Financial time series data specially stock market data is very hard in decomposition and forecasting because the data are non-linear and non-stationary with high heteroscedasticity (Tabachnick and Fidell, 2001; Pai and Lin, 2005; Wang, et al., 2012; Wei, 2013). The future plan of the investors is to improve their profits without risk. This issue encourages the researchers to develop many forecasting models (Tabachnick and Fidell, 2001; Atsalakis, et al., 2011) such as artificial neural network model (ANNs) for more details refer to (Tabachnick and Fidell, 2001; Mitra, 2009; Atsalakis and Kimon, 2009; Mohamed, 2010; Maqableh and Karajeh, 2014; Maqableh et al., 2015), some hybrid models have modified for more details refer to (Wang, 2011; Awajan et al., 2017). ARIMA model which is an old model but still has widely application in financial time series field (Kyungjoo, et al., 2007; Merh, et al., 2010; Sterba and Hilovska, 2010). This model is considered as the forecasting process and can be implemented from two steps which are statistical and artificial intelligence techniques (Tabachnick and Fidell, 2001). As a critically review, many models have been used in predicting such as exponential model, regression method, GARCH model and others. However, few related works that has used ARIMA model for forecasting stock market data for more details refer to (Meyler et al., 1998; Javier et al., 2003; Nochai & Nochai, 2006; Khasel et al., 2009; Lee and Ho, 2011; Wang, 2011; Khashei et al., 2012). However, some researchers have used ARIMA model in forecasting some of financial data such as (Alwadi, 2015).

ARIMA model is a statistical method which used for decomposing and predicting time series data by modeling the correlations in the data. In real data application, there are some advantages of the ARIMA model especially short term predicting (Box and Jenkins, 1970). Moreover, the ARIMA method only needs the prior data of a time series data or stock market data to generalize the forecast. Hence, the ARIMA method can improve the forecast accuracy while stilling the number of parameters to a minimum. While, there are some disadvantages of the ARIMA model such as: in the model identification techniques for identifying the correct model from the class of possible models are hard or maybe undefined, the theoretical model of the ARIMA model and structural relationships are not distinct as some simple forecasts models such as simple exponential smoothing and Holt-Winters (Donovan, 1983). Finally, this model in the long term forecasting is poor model at predicting series with turning points. However, these disadvantages will not effect on the direction of this research.

In this article the researcher applying ARIMA model for short term closed stock market data and some results of forecasting are obtained. The results gotten from real data established the potential asset of ARIMA model to offer for the investors short-term forecasting that could assistance investment decision making. This article is organized as: Section 2 presents brief overview of mathematical models used. Section 3 presents the results obtained and the methodology used. Finally, in section 4 is the conclusion.

2. Mathematical Models

2.1 Autoregressive Integrated Moving-Average Model (ARIMA (p,d,q))

The auto-regressive moving average (ARMA) models are used in stationary stock market data only, this model contains three combination models which are (Awajan et al., 2017; Box and Jenkins, 1970):

1) autoregressive (AR) model and a moving average
2) (MA) model.
3) $\{e_t\}$: white noise (WN) process,

A time series $\{Y_t\}$ is said to follow the ARMA(p,q) model if:

$$Y_t = \grave{\imath} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} \dots + \phi_p Y_{t-p} + e_t - \grave{e}_1 e_{t-1} - \grave{e}_2 e_{t-2} \dots - \grave{e}_q e_{t-q}$$

Where p and q are greater than zeros, prefers to autoregressive part (AR), q refers to moving part (MA) and $\{e_t\}$ is the white noise. An extension of the ordinary ARMA model is the auto-regressive integrated moving-average model (ARIMA(p,d,q)) given by :

$$\phi_p(B)(1-B)^d Y_t = \grave{e}_0 + \grave{e}_q(B) e_t$$

Where p, d and q denote orders of auto-regression, integration (differencing) and moving average, respectively. When d=0, the ARIMA model reduces to the ordinary ARMA model

2.2 Accuracy Criteria

This section consists of two subsections. Firstly, we will present the criteria which have been used to make a fair comparison. The researchers have been adopted to compare the performance of the models within one type of accuracy criteria which is Root Mean Squared Error. For more details about the mathematical model refer to (Awajan et al., 2017; Jaber, et al., 2017).

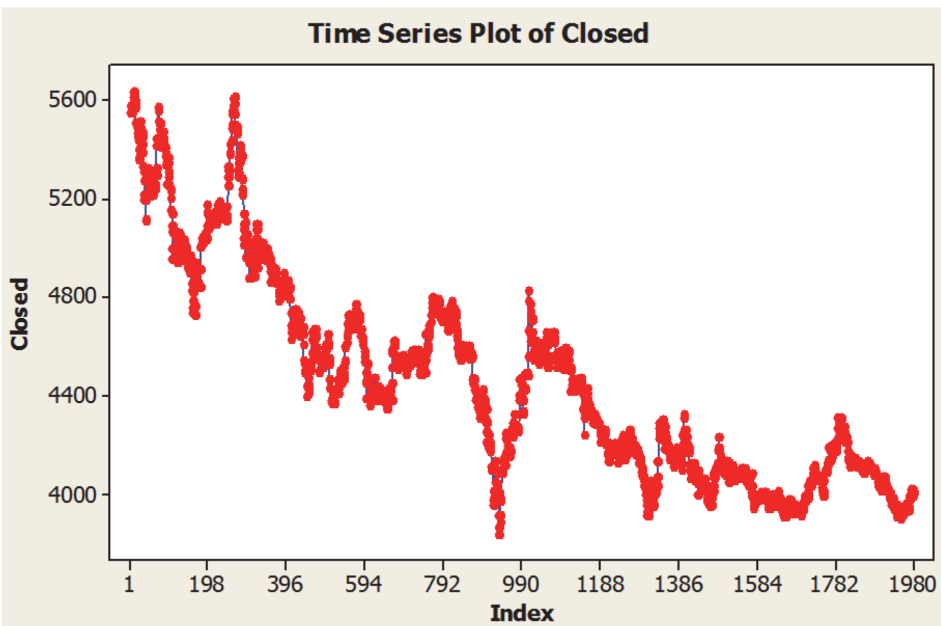

Figure 1. Diagram of the dataset

3. Methodology, Results and Discussion

The methodology of this article is to use the fit ARIMA model for closed stock market data in order to implement a fitted forecasting model. The MINTAB software is the tool used to get the results. The daily price index of Amman Stock Exchange (ASE) for a specific period of time has been selected as the statistical population; about 2000 observations were accumulated for each variable from related databases in the mentioned period. Figure 1 shows the diagram of the dataset.

We notice that the data are non- stationary since it not fluctuated around constant mean and variance and there is some attractive events such as at the observations number: 198, 200, 250, 900, 1000 then the data become stable after the observation number1200 which indicate that the external variables are less effect than before the observation number 1200.

To find the fitted ARIMA model. Therefore, RMSE is selected as criteria since there are many ARIMA models can be established for one column of dataset based on using different values of p,d and q. Therefore, the fitted ARIMA model has less RMSE. The following Table will show all the possible fitted ARIMA models with its RMSE.

Table 1. Possible ARIMA models with its RMSE

ARIMA	RMSE	ARIMA	RMSE	ARIMA	RMSE
(0 , 0 ,0)	Not fitted	(0 , 2 ,0)	Not fitted	(1 , 1 ,2)	4.7
(0 , 0 ,1)	4.3	(0 , 2 ,2)	4.1	(1 , 2 ,0)	Not fitted
(0 , 0 ,2)	Not fitted	(1 , 0 ,0)	Not fitted	(1 , 2 ,1)	4.1
(0 , 1 ,0)	Not fitted	(1 , 0 ,1)	4.8	(1 , 2 ,2)	4.6
(0 , 2 ,0)	Not fitted	(1 , 0 ,2)	Not fitted	(2 , 0 ,0)	Not fitted
(0 , 1 ,1)	Not fitted	(1 , 1 ,0)	Not fitted	(2 , 0 ,1)	4.4
(0 , 1 ,2)	4.7	(1 , 1 ,1)	5.00	(2 , 0 ,2)	4.7
(2 , 1 ,0)	Not fitted	(2 , 1 ,2)	5.1	(2 , 2 ,1)	4.9
(2 , 1 ,1)	4.00	(2 , 2 ,0)	Not fitted	(2 , 2 ,2)	4.2

Based on Table 1 the researchers note that:

The values of p,d and q are between 0 and 2 only since these values impossible to be in the minus also theses values should not be more than 2 since the estimation of the parameters will be worthless.

RMSE is varied between 4.00 and 5.00 based on the dataset used. Therefore, After the dataset is implemented using the software then ARIMA (2,1,1) was found the best with RMSE= 4.00.

In some cases ARIMA model is not fitted which means that the estimation of the dataset cannot be done then it should be ignored.

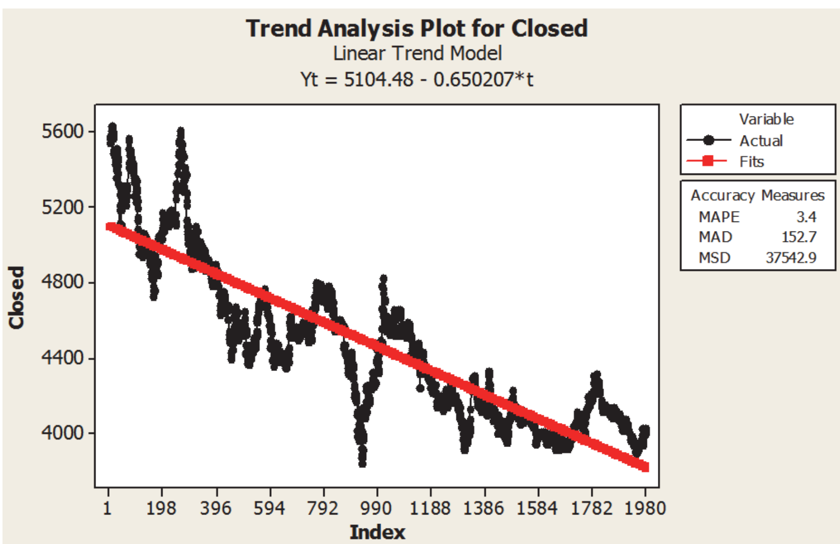

Figure 2. The trend analysis

The trend analysis as shown in Figure2 is very important in forecasting processes in order to show the direction of the future values and the stationarity of the dataset. Then finally, the values of ARIMA parameters with its significant level can be summarized as:

Type	Coef	SE Coef	T	P-value
MA 1	-1.5371	0.0120	-128.18	0.000
MA 2	-0.8955	0.0093	-95.81	0.000
Constant	4460.78	10.04	444.10	0.000

We notes that all the parameters (MA and the constant term) are significant since the P-value is 0.00 for all the variables which means the selected model is very fit and suitable for forecasting.

4. Conclusion

Based on the results in the tables and figures then this paper shows three major results can be summarize as:

The general process of ARIMA model for closed stock market data predicting. The results achieved with best ARIMA model which is ARIMA (2,1,1) with RMSE= 4.00 while the other models of the ARIMA has higher than this value. Moreover, the fluctuation of the data set is discussed and all of the outlier values have been detected. These results guide investors in this area to make profitable investment decisions since these results found that ARIMA model can participate reasonably well with emerging forecasting techniques in short term forecasting. The limitation for this model is in using ARIMA model with only short term forecasting. However, in some cases the researchers need to make long term forecasting. As a future work, this model can be implemented for any other type of data such as rainfall data.

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