International Journal of Scientific Engineering and Applied Science (IJSEAS) – Volume-2, Issue-10, October 2016
ISSN: 2395-3470
www.ijseas.com

Forecasting Next Day Financial Time Series Data

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Abstract

In 2015, Ragda (2015) discussed the future situation for the past data in the context of the Department of Land and Survey, Ministry of Finance, Jordan. However, this article continues the work done in 2015 in order to predict the future event using dataset have collected from Department of Land and Survey for the year 2017. Some stock market data was obtained from the Department of Land and Survey in Jordan will be implemented using ARIMA model the model, the finding shows that will be no changes in the direction of the behavior of the Department of Land and Survey, Ministry of Finance, Jordan and this department should be change its policy.

Keywords: *financial time series, forecasting, ARIMA model*

1. Introduction

Stock market predicting is important in investment, and it has a high consideration in financial time series data. Generally, forecasting stock market has become complicated because different from demand series, price series include characteristics such as non-stationary and nonlinear behavior

Mainly, commodity prices from the data from stock market have abrupt change and trends. Therefore, we need a good model in order to forecast these irregular behaviors.

Subsequently, researchers have used many mathematical models such as: curve fitting log transforms, differencing, Fourier transform, and wavelet transform to get a smooth data. Recently, ARIMA model has been raised very rapidly in the short term forecasting processes. For instance, Wall Street analysts have used ARIMA model as a mathematical models to forecast the future behavior in their financial data. For more details about the forecasting, especially the forecasting using ARIMA model, please refer to (Swider and Weber, 2007; Contreras et al., 2005; Spyros Makridakis et al., 2002; Radga Alwadi, 2015; Al Wadia and Tahir Ismail, 2011; Al Wadi et al., 2011; Ababneh et al., 2013; Ismail et al., 2011; Alwadi, 2015; Al Wadi et al., 2013; Ismail et al., 2010; Al Wadi et al., 2010; Al Wadi, et al., 2010; Al-Khazaleh, et al., 2015; Al Wadi, et al., 2013; Al Wadi, 2010; and Al Wadi, 2010).

Consequently, to show the effectiveness of ARIMA model in the context of predicting, this paper uses this model to obtain results which is a valuable indicator for the investor in the land and the survey sector. Moreover, in order to illustrate the effectiveness of this model, some data sets have to be collected from the website: http://www.dls.gov.jo/EN/index.php (Department of Land and Survey, Jordan). In addition, we consider a past time series data during last two years (2013, 2014, 2015, and 2016) in order to forecast the behavior of the year 2017. Then, this decrease which will continue the next year would be noticed.

This paper consists of 4 sections. Section 2 has some definitions, literature review, and mathematical concepts; section 3 shows the empirical results and discussion; and section 4 presents the conclusion.

2. Mathematical and Literature Reviews

2.1. ARIMA Model

ARMA is a suitable model for the time series data. Moreover, many of the software use least square estimation which needs to be stationary. To overcome this problem and to allow the ARMA model to grip non-stationary data, the researchers explore a singular class for the non-stationary data. Thus, this model is called Auto-regressive Integrated Moving Average (ARIMA). This idea is divided into a non-stationary series one or more times until the time series becomes stationary, and then the fit model is found. ARIMA model has got very high attention in the scientific world. However, this model is popularized by George Box and Gwilym Jenkins in 1970s (Swider & Weber, 2007; Contreras et al., 2005; Spyros Makridakis et al., 2002; Radga Alwadi, 2015; Al Wadia & Tahir Ismail, 2011; Al Wadi et al., 2011; Ababneh et al., 2013; Ismail et al., 2011; Al wadi, 2015). Also, there are a huge number of ARIMA models. Generally, there are ARIMA (p, q, d) where:

P: order of autoregressive part (AR), d: degree of first differentiation (I), q: order of the first moving part (MA). Note that if no differencing is done ($d = 0$), then the ARMA model can be gotten from ARIMA model (Swider & Weber, 2007; Contreras et al., 2005; Spyros Makridakis et al., 2002; Radga Alwadi, 2015; Al Wadia & Tahir Ismail, 2011; Al Wadi et al., 2011; Ababneh et al., 2013; Ismail et al., 2011; Al Wadi et al., 2010; Al Wadi et al., 2010; Alwadi, 2015). Therefore, the equation for the simplest case ARIMA (1, 1, 1) is as follows:

$$(1-\Phi_1 B)(1-B)Y_t = c + (1-\theta_1 B)e_t.$$

The model building process involves the following steps:

- **Model Identification**

This is the first step which is used to determine whether the time series data is stationary or non-stationary.

- **Model Parameter Estimation**

The estimation of parameters is very significant in the model building. The parameters which are thus obtained are estimated statistically by the method of least squares.

- **Model Diagnostics**

Before forecasting the series, it is necessary to check the adequacy of the tentatively identified model. The model is declared to be adequate if the residuals cannot improve forecast anymore. In other words, residuals are random.

- **Forecasting**

Once the model adequacy is established, the series in question shall be forecasted for a specified period. Thus, it is always advisable to keep track of the forecast errors; and depending on the magnitude of errors, the model would be re-evaluated. Therefore, in order to select the best ARIMA model, we should select the best criteria as mentioned below.

2.2. Methodology

The criteria which have been used to make a fair comparison can be presented in this subsection. The framework comparison can be presented with more details as follows:

However, we adopted to compare the performance of the models within two types of accuracy criteria; Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). These types of accuracy can be illustrated as (Aggarwal et al. (2008)):

1- Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\text{actual value-predicted value})^2}{N}}.$$

2- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\text{actual value-predicted value}}{\text{actual value}}\right|.100\%$$

Where N represents the number of observations

3. Experimental Results

The least value of the used criteria was selected to find the fit ARIMA model of the choice data from the Department of Land and Survey. All ARIMA models should be in (0,0,0) and (2,2,2). There is no need for more than (2,2,2). Thus, this is because it is not suitable mathematically and ARIMA model would become valueless. Therefore, the best ARIMA model is selected as mentioned the table below.

Table1. Fit ARIMA (p,d,q) Model

Statistical fit	Year 2013	Year 2014	Year 2015	Year 2016	Year 2017
RMSE	1.2	1	0.8	1.7	0.798
MAPE	1.2%	0.9%	0.8%	0.92%	0. 69%

Mathematically, the similar sample data was picked for fair comparison. The appropriate ARIMA model for predicting the sample data was also picked. Regarding the results from Ragda (2015), year 2013 had ARIMA (1,2,2) with RSME equal to 1.2 as presented in Table 1. Then, year 2014 had ARIMA (1,2,1) with RMSE equal to 1. Similarly, the year 2015 had a suitable ARIMA (1,1,1). Finally, Year 2016 has ARIMA (1,1,2) with RMSE equal to 1.7. However, the expected values for the ARIMA for the year 2017 will be ARIMA (2,1,2) with RMSE of 0.798.

Mathematically, two important conclusions can be summarized. Firstly, the forecasting accuracy was evaluated using the suitable ARIMA model since the forecasting with ARIMA produces less RMSE which will be a good indicator about future events.

Empirically, the result in this article leads us to conclude that in the next year (2017), we will have the same result as the year 2013, 2014, 2015, and 2016. However, this is because the accuracy forecasting results are almost similar. Therefore, we recommend the department to change some of their policy in order to improve its forecasting accuracy and its income for the next year.

4. Conclusion

The overall objective of carrying out this study is to fit the suitable ARIMA models in forecasting a sample dataset was taken from the Department of Land and Survey. Based on the findings of the experiments, the significant contributions of this study can be summarized as follows:

1- The experiments have shown that the level of forecasting accuracy with suitable ARIMA model was calculated for the year 2017.

2- Some recommendation about the department's policy has mentioned by changing in the direction of the behavior of the Department of Land and Survey, Ministry of Finance in order to encourage the invertors to make some investment in Jordan.

5. References

Swider D.J. and Weber, C., Extended ARMA models for estimating price developments on day-ahead electricity markets, Electric Power Systems Research, 77(2007), 583-93. Contreras, J., R. Espinola, F.J. Nogales and A.J.

Conejo, ARIMA models to predict next-day electricity prices, IEEE Transactions on Power Systems, 18(2005), 1014-20. SAS/ETS® 9.22 User's Guide, SAS Institute Inc, 2010.

Spyros Makridakis, C. Wheelwright and J. Hyndman, Forecasting methods and applications, Third edition, Wiley& Sons, Inc, New York, (1998).

S. Skander, On the Use of the Wavelet Decomposition for Time Series Prediction, Neurocomputing, 48 (2002), 267–277.

Radga Alwadi. Forecasting short term financial data. European Scientific Journal. 11(2015), 251-255.

S. Al Wadia, M Tahir Ismail. Selecting wavelet transforms model in forecasting financial time series data based on ARIMA model. Applied Mathematical Sciences, 7 (2011), 315-326.

S Al Wadi, MT Ismail, SA Abdul Kari. Discovering structure breaks in Amman stocks market. Journal of Applied Sciences, 11 (2011), 1273-1278.

F. Ababneh, S. Al Wadi, MT Ismail. Haar and Daubechies wavelet methods in modeling banking sector. International Mathematical Forum, 8 (2013), 551-566.

MT Ismail, SAA Karim, S. Alwadi A study of structural breaks in Malaysian stock market. African Journal of Business Management, 5 (2011), 2418.

S. Al Wadi, MT Ismail, SAA Karim. A comparison between Haar wavelet transform and fast Fourier transform in analyzing financial time series data. Res J Appl. Sci., 5 (2010), 352-360.

S. Al Wadi, MT Ismail, SAA Karim. Volatility Computational in Financial Time Series Data Based on Wavelet Transforms. International Journal of Mathematics & Computation, 7(2010), 102-113

S. Alwadi. Existing outlier values in financial data via wavelet transform. European Scientific Journal, 11 (2015), 245-254.

S. Al Wadi, A Hamarsheh, H Alwadi. Maximum overlapping discrete wavelet transform in forecasting banking sector. Applied Mathematical Sciences, 7 (2013), 3995-4002.

M.T. Ismail, S. Al Wadi and S.A.A. Karim, "Forecasting Malaysia stock market based on wavelet transformation using box-jenkins model", Research in Mathematics and Economic, 2010.

S. Al Wadi, M.T. Ismail and S.A.A. Karim, "A comparison between the daubechies wavelet transformation and the fast fourier transformation in analyzing insurance time series data", Far East Journal of Applied Mathematics, 45 (2010), 53-63.

Al-Khazaleh, S. Al Wadi, F Ababneh. Wavelet Transform Asymmetric Winsorized Mean in Detecting Outlier Valuesamh. Far East Journal of Mathematical Sciences, 96 (2015), 340-351.

S Al Wadi, F Ababneh, H Alwadi, MT Ismail. Maximum Overlap Discrete Wavelet Methods in Modeling Banking Data. Far East Journal of Applied Mathematics, (2013).

S. Al Wadi, M.T. Ismail and S.A.A. Karim, "Statistical computational of volatility in financial time series data world academy of science", Engineering and Technology, 62 (2010)778-782.