Forecasting the Stock Indexes of Fragile Five Countries through Box-Jenkins Methods

Sedat Yenice, PhD
Assist. Prof.
Gazi University
Vocational School of Social Sciences
06310 Ankara Turkey

Mustafa Agah Tekindal, PhD
Assist. Prof.
Izmır University School of Medicine
Department of Biostatistics
35350 Izmir Turkey

Abstract

The main aim of this study is to forecast the prospective daily closing values of the stock indexes of Turkey, Brazil, Indonesia, South Africa, and India that are referred to as developing countries and are called fragile five in the report prepared by Morgan Stanley in 2013. Another aim is to determine whether or not similar index forecasts will be provided for these countries. To this end, 3-year daily index closing data of these countries were used as dataset, and an attempt was made to create forecasting models through ARIMA method. ARIMA models created for all countries were found to be significant and have quite low margins of error. The closing values forecasted via the created models and the actual closes were compared, and the following was realized: The model created for Turkey forecasted with an accuracy rate of approximately 72%; that created for Brazil forecasted with an accuracy rate of approximately 65%; that created for Indonesia forecasted with an accuracy rate of approximately 74%; that created for South Africa forecasted with an accuracy rate of approximately 66%; and that created for India forecasted with an accuracy rate of approximately 59%.

Keywords: Stock Index, ARIMA, Index Forecasting, Fragile Five

1. Introduction

Indexes are measures that are useful for measuring changes which consist of one or more variable and thus are good for giving general information about complicated events which are based on a lot of variables and are difficult to understand by attributing them to a single variable (Karan, 2001:p.55). In the most general sense, indexes are the indicators that express changes in prices. The most common use of indexes is stock indexes that show the trend of prices calculated in stock exchanges and occurring in stock exchanges. The best information about the situation of a stock exchange and the general trend of prices is provided by stock indexes. They are frequently used in economic analyses as indicators as they demonstrate information about and movements of stock exchanges. In stock exchanges (especially in share markets), indexes express changes in a lot of share prices with a single figure. If it were not for index, it would not be possible to determine in what direction and how much a market moves (Aksoy, 1991,p:249) As all or some of the shares in the market are taken into account during the formation of indexes, indexes are perceived as a portfolio made up of these shares. Thus, the trends of indexes in the course of time and their prospective situations are always objects of interest.

Since index forecasting is important, a lot of studies have been conducted on this subject in finance literature. A lot of theories aimed at explaining the movements of financial markets and some statistical forecasting models aimed at predicting the future movements of financial markets have been introduced so far (Avcı and Çinko, 2008, p. 198)Though there is no method that can precisely forecast the movements involving stock indexes, literature contains many studies on this subject. While some of these studies are based on statistical modeling methods, some others are based on data mining.

The present study aims to forecast the prospective stock indexes of different countries through ARIMA model and determine whether or not the stock indexes of fragile five countries have similar trends as stated in Morgan Stanley's 2013 report. To this end, an attempt was made to model the prospective movements of the indexes through ARIMA method, and then the index forecasts obtained through modeling were compared with the actual indexes. In this paper, the introduction section is followed by literature review. Then come data and research method. Finally, the obtained findings are presented, and a general evaluation is made.

2. Literature Review

Literature contains many studies dealing with the forecasting of stock indexes. In general, these studies employ artificial neural networks models, support vector machines, and hybrid methods involving the collective use of these two methods. Some of the studies are summarized below along with their results. Tayyar and Tekin (2013) used support vector machines in order to forecast the direction of movement of BIST 100 index and then employed logistic regression method to classify support vector machines. The direction of movement of the index was forecasted through the obtained model with an accuracy rate of 70%. Similarly, Demirci et al. (2011) used vector machines and logistic regression methods in order to forecast the direction of return of BIST 100 index. They forecasted through vector machines method with an accuracy rate of 86% and concluded that this method can be used for index forecasting as an effective alternative. Pai and Lin (2005) used a hybrid methodology composed of ARIMA model and SVM model to forecast stock price problems. It is believed that this hybrid model substantially improves the stock price forecasting performance showed by ARIMA model or SVM model alone. These authors think that hybridization of two different models (theoretical and empirical) reduces forecasting errors. Similarly, Zhang (2003) proposes a hybrid methodology combining ARIMA and ANN models in linear and non-linear modeling. It is reported in this study that the hybrid model is an effective way of improving the forecasting accuracy achieved by any one of the models making up it individually.

Tosunoğlu and Benli (2012) tried to forecast the monthly values of Morgan Stanley Capital International index through artificial neural networks method. They concluded that index values are successfully forecasted through neural networks method. Aygören et al. (2012) tried to forecast BIST 100 index through ARMA model, Newton's numerical searching model, and artificial neural networks method. They concluded that ARMA model and Newton's numeric searching model are less successful than artificial neural networks technique in index forecasting. Avcı and Çinko (2008) aimed to forecast the daily index returns in the stock exchanges of 6 developing countries through artificial neural networks model. They concluded that the feed forward artificial neural networks models in 3 different structures which they used in their research did not have any superiority to each other. They also found out that the forecasting performance of the artificial neural networks models did not vary by market, but varied by period and place of application. Altay and Satman (2005) compared the forecasting performance of ANN and linear regression strategies in the case of Borsa Istanbul and obtained some evidences proving that ANN models are statistically and financially superior. In their research, ANN models forecasted stock index marks (signals) for daily, weekly, and monthly data at accuracy rates of 57.8%, 67.1%, and 78.3% respectively. They concluded that when ANN models are used as trading strategies, they are more successful than linear regression models.

Diler (2003) tried to forecast the next-day direction of BIST 100 index through artificial neural networks method. The next-day direction of BIST 100 index was forecasted with an accuracy rate of 60.81%. Boyacioglu and Avcı (2010) attempted to forecast stock market returns through Adaptive-Network-Based Fuzzy Inference System (ANFIS). They tried to model and forecast stock market price index return in Borsa Istanbul through ANFIS. The model successfully forecasted the monthly return of Borsa Istanbul Bist 100 Index with an accuracy rate of 98.3%. Armano et al. (2005) proposed a new approach for forecasting stock indexes. Forecasting in that study was based on the interaction of the group composed of experts each of whom integrated genetic and neural technologies. Each one of these experts had a genetic classifier designed to control the activation of a feed forward artificial neural network to do a local forecasting. They concluded that the approach had a high capability to forecast and performed better than "Buy and Hold" strategy again and again. Chen et al. (2003) aimed to model and forecast the direction of the market index return of Taiwan Stock Exchange. The statistical performance of probabilistic neural network (PNN) forecasting was measured, and comparison was made through generalized method of moments (GMM) with Kalman filtering. They concluded that PNN-based investment strategies provided higher returns than other investment strategies.

The difference of the present study from other studies in literature is that it attempts to forecast the daily closing values of indexes through ARIMA model. In addition, it is thought that a contribution will be made to literature through the administration of forecasting models to the indexes of fragile five countries indicated in Morgan Stanley's report and the search of whether or not the movement of direction of the stock indexes of these countries is the same.

3. Dataset and Methodology

3.1. Dataset

The daily stock index closing data of 5 countries (i.e. Brazil, India, Indonesia, Turkey, and South Africa) were used for forecasting stock indexes. These 5 countries are called fragile five in the report prepared by Morgan Stanley in 2013. These fragile five countries are abbreviated as BIITS. According to the report prepared by Morgan Stanley, fragile five countries have a high current ratio and inflation and unstable performance. These countries having similar characteristics were grouped in this way after FED made some decisions on bonds and announced them. After FED signaled its tapering intention on the 22nd of May 2013, the currencies of these 5 countries decreased in value against foreign currencies. As a result, bond yields increased, and stock exchanges suffered substantial losses in value. As these countries reacted to the tampering decision of FED in the same direction, they were named fragile five in the grouping done by Morgan Stanley in the report prepared in 2013.
Literature contains a lot of studies in which data concerning fragile five countries are used. Akel (2015) investigated the cointegration and causality relationships among the stock indexes of fragile five countries and detected short-term and long-term significant relationships. Similarly, Aktan and (2009) investigated the relationships of stock exchanges of Brazil, Russia, India, China, and Argentina with one another and with the US markets and concluded that the US markets have a significant effect on the markets of other countries in the short term. Bozoklu and Saydam (2010) investigated the integration of the stock exchanges in Brazil, China, India, Russia, and Turkey and concluded that the stock exchanges of these countries are integrated. As is seen above, literature contains a lot of studies on the integration and cointegration of fragile five countries and similar countries, but there is no need to explain all of them here.

The fragile five countries (BIITS) are used in this study to determine whether or not these countries move in the same direction as indicated in the report prepared by Morgan Stanley. The dataset of the present study consists of the daily closing prices of base indexes in the stock exchanges of 5 countries between 01.01.2012 and 31.12.2014. The data were obtained from investing.com. The indexes used in the study are as follows;

Brazil = Sao Paulo Stock Index (BVSP)
Indonesia = Indonesia Stock Index (IDX)
India = S&P Bombay Stock Index (BSESN)
South Africa = Johannesburg Stock Index (JTOPI)
Turkey= Borsa Istanbul 100 Index (XU100)

The analysis data used in the study are the closing data calculated on a daily basis and are expressed in each country's own currency. Since the index values of countries stand as indicators, there is no need to convert all of them into the same currency.

3.2. Method

Autoregressive Integrated Moving Average (ARIMA) method used in forecasting time series events was developed by Box and Jenkins (Box and Jenkins, 1976). ARIMA modeling approach is limited to the assumption that there is linearity between the variables. Apart from that, the researchers developed alternative modeling perspectives for forecasting the time series events not fulfilling the linearity assumption. ARIMA or Box-Jenkins models are the combinations of AR and MA models administered to the series differenced at degree d. The essence of the Box-Jenkins method is the choice of an ARIMA model that is the most suitable one among various models based on the structure of the current data but contains limited number of parameters. As a whole, these models are represented as ARIMA (p, d, q).

In the models (Işığıçok, 1993, 42),

p: Degree of autoregressive model,
q: Order of moving average model,
d: Degree of non-seasonal differencing.

The expression of ARIMA (p, d, q) model can be defined as indicated in equation (1) (Tekindal, 2008):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + ...+ \phi_P Z_{t-P} + a_t - \theta_1 a_{t-1} - a_t - \theta_2 a_{t-2} - ....- a_q - \theta_q a_{t-q} \qquad (1)$$

Here:

ϕ_P: Parameter values for autoregressive operator, a_t: Error term coefficients, θ_q: Parameter values for moving average operator, Z_t : Time series of the original series differenced at degree d. In other words, $W_t = Y_t - Y_{t-1}$,t = 1,2,…,t (2)

The first differences series is defined as given in the equation (2). Here:

W_t = The first differences series,

Y_t = The random variables subset of the original time series.

If the first differences series is not stationary, stationary is checked by differencing the first time series again. This is modeled as given in equation (3).

$$Z_t = W_t W_{t-1} \qquad t = 1,2,\ldots,t \qquad (3)$$

When the degree of differencing is d = 0 (that means that the original series is stationary), ARIMA model will be AR, MA, or ARMA model. Due to this feature, it can be said that ARIMA models incorporate all of the Box-Jenkins models. As done by ARIMA (p, d, q) model, seasonal ARIMA(P,D,Q)s models only distinguish the interval between the observations that effect one another. These are s(seasonal) periods. They do not indicate period involving a single interval.

For example: ARIMA(1,0,0)12 model is [monthly AR(1)]].

$$Zt = \alpha + \phi 1\ Zt\text{-}12 + At \qquad (4)$$

Thus, autocorrelation decrease exponential lags may be at 12, 24, 36, etc.

Partial autocorrelation lag is 12 = $\phi 1$

If lag is after 1, it becomes equal to 0.

Seasonal ARIMA(P,D,Q)s Models ARIMA(p, d, q) Models relationship can be expressed as SARIMA models:

$$\Phi P(B)\ \phi p(B)\ [1\text{-} B^s\ ]^D\ [1\text{-}B]\ ^d Zt = \alpha + \Theta Q(B)\ \theta q(B)\ At \qquad (5)$$

This model is used if we want to understand what is meant by autocorrelation design through two autoregressive polynomials and two moving average polynomials and it is difference operator (Schwert, 2008;8).The model establishment process involves certain repetitive steps (Box and Jenkins, 1976, 251). These steps are indicated in the flow chart given in Figure 1.

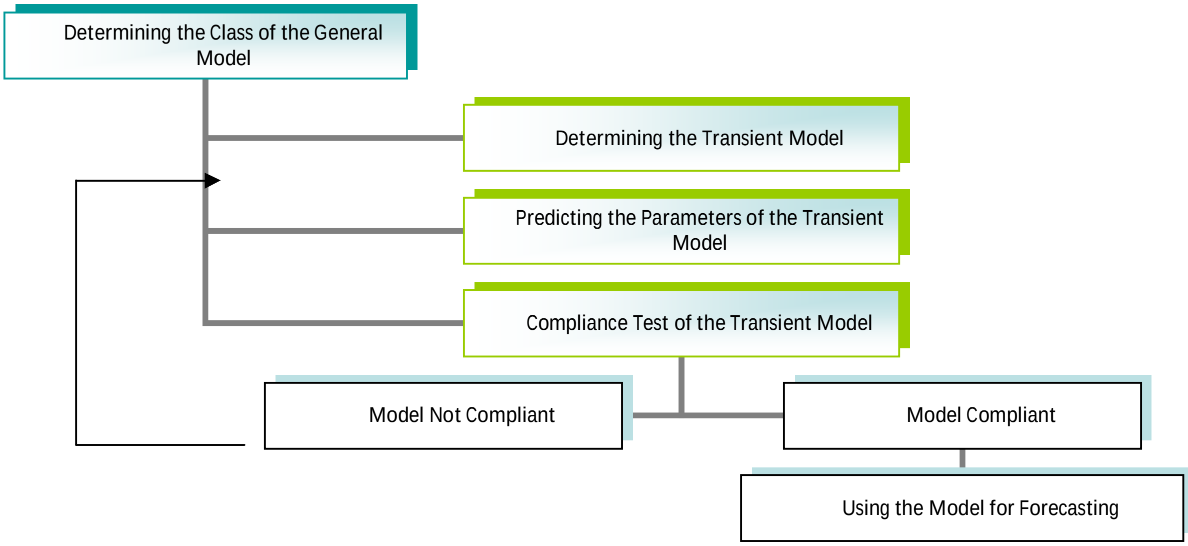


Figure 1: Model Establishment Process

The establishment of Box-Jenkin ARIMA models involves four main steps. In the first step, the class of the general model is determined. In selecting the general model, the graphs of autocorrelation and partial autocorrelation functions are used. The features of theoretical functions concerning ARIMA models are used based on autocorrelation and partial autocorrelation functions in Figure 1 (Yaman et al., 2001, 27). In the second step, a transient model compliant with the structure of the data is determined. To this end, autocorrelation and partial correlation functions are used. In determining the model, a model is selected from model classes such as AR, MA, ARMA, ARIMA, and SARIMA. In the third step, the parameters of the transient model are forecasted by use of efficient statistical techniques, and the standard errors of coefficients are calculated to test whether or not they are significant. In the last stage, compliance of the model is checked for forecasting. To this end, the autocorrelation function of the model is examined by drawing the graph of the autocorrelation coefficients of the errors of the transient model that is assumed to be compliant. If this function displays a particular shape, it is concluded that errors are not random. This kind of a finding means that the determined transient model is not compliant. Therefore, one turns to the second step again, and this process is repeated until the compliant model is determined through a new transient model. The model passing the compliance check is now ready to be used for forecasting (Yaman et al., 2001, 27).

Valid criteria to test model validity.

- Forecast Error (e):

$$\mathbf{e}_t = \mathbf{A}_t - \mathbf{F}_t \qquad (6)$$

- Mean Forecast Error (MFE or Bias):

$$MFE = \frac{\sum_{i=1}^{n} e_i}{n} \qquad (7)$$

- Mean Absolute Deviation (MAD):

$$MAD = \frac{\sum_{i=1}^{n} |e_i|}{n} \qquad (8)$$

- Mean Absolute Percentage Error (MAPE):

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad (9)$$

• Mean Square Error (MSE):

$$MSE = \frac{\sum_{T=1}^{n} E_t^2}{N} \quad (10)$$

A MAPE value of ≈ 10% is acceptable (Tekindal, 2008,135-153).

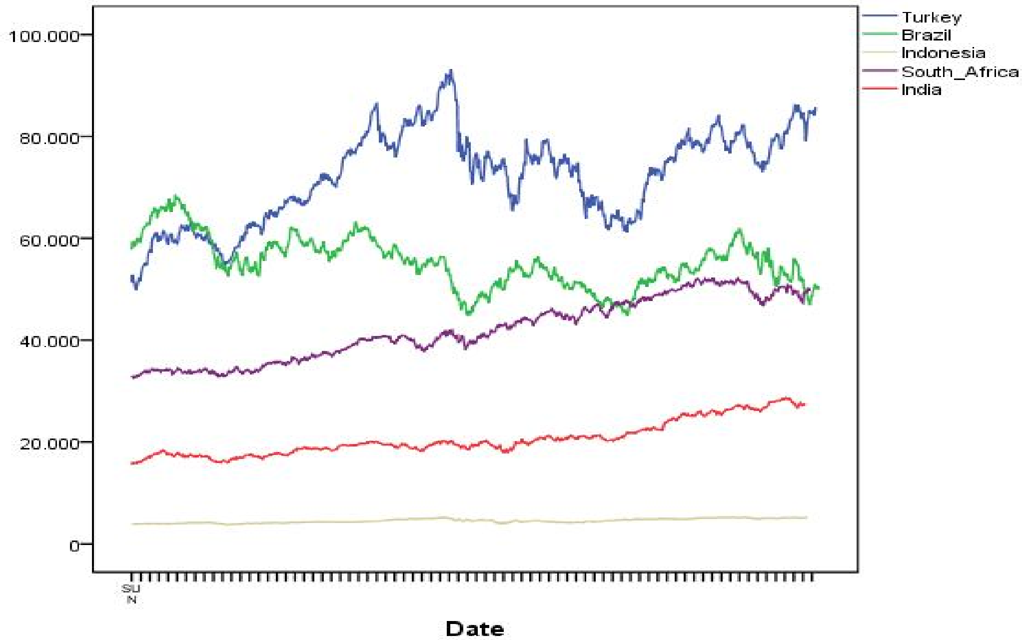


Figure 2: The plot graphs of original values

The Figure 2 indicates that logarithmic and non-seasonal difference transformation is needed in all countries. In addition, ADF unit root test was administered to the index closing values of all countries. According to the unit root test results, the data are not stationary. This being the case; firstly logarithmic difference corrections and then, if stationary is not achieved, non-seasonal difference corrections are needed.

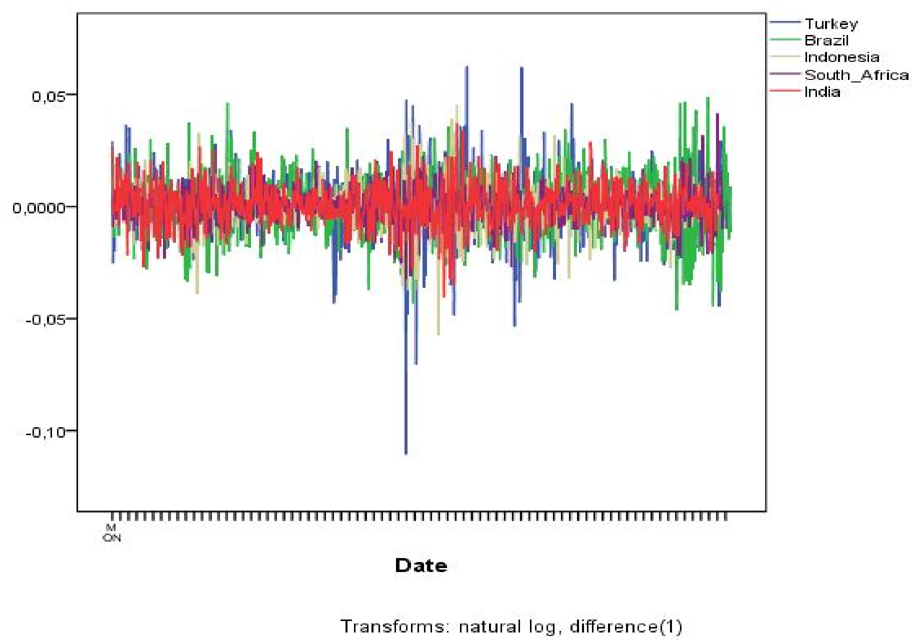
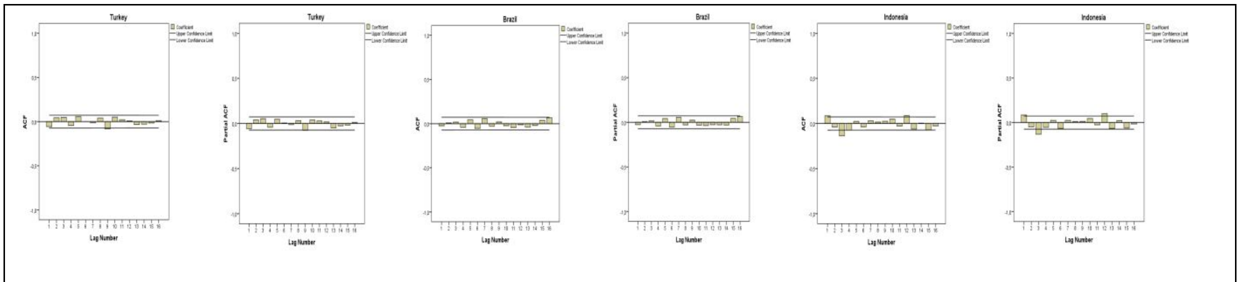


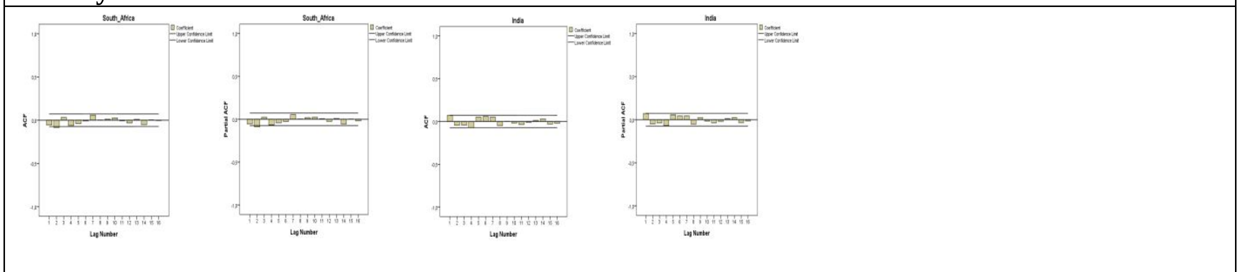
Figure 3: The Plot of the Data after Logarithmic and Non-seasonal Differencing

Figure 3 shows that the data are almost stationary. That means that the data are now suitable to draw ACF and PACF graphs that are to allow us to forecast the coefficients of the relevant model.



acf pacf acf pacfacf pacf

Turkey **Brazil** **Indonesia**



acfpacfacfpacf

South Africa **India**

Figure 4: The ACF and PACF graphs of the data following seasonal and non-seasonal differencing

Figure 4 guides us through the selection of ARIMA models. In this case, ACF graphs help us make predictions about the coefficient of the MA model while PACF graphs help us make predictions about the coefficient of AR model.

Table 1: The Most Suitable ARIMA Models for the Countries

Country	Model	Equation Significance	MAPE
Turkey	ARIMA(2,1,0)	$0.282 > \alpha$	1.057
Brazil	ARIMA(3,1,0)	$0.141 > \alpha$	1.067
Indonesia	ARIMA(3,1,0)	$0.049 < \alpha$	0.734
South Africa	ARIMA(2,1,0)	$0.282 > \alpha$	0.615
India	ARIMA(3,1,0)	$0.396 > \alpha$	0.700

The Table 1 summarizes the most suitable forecasting models for country indexes. The Table 1 also presents MAPE values representing error rates along with the models. As is seen in the Table 1, the error rate of the model calculated for Turkey is approximately 1.05%; the error rate of the model calculated for Brazil is approximately 1.06%; the error rate of the model calculated for Indonesia is approximately 0.73%; the error rate of the model calculated for South Africa is approximately 0.61; and the error rate of the model calculated for India is approximately 0.7%. The fact that MAPE values are quite low increases the reliability of the forecasting models created based on country indexes. The predictions made based on the models created in the study are summarized below by country.

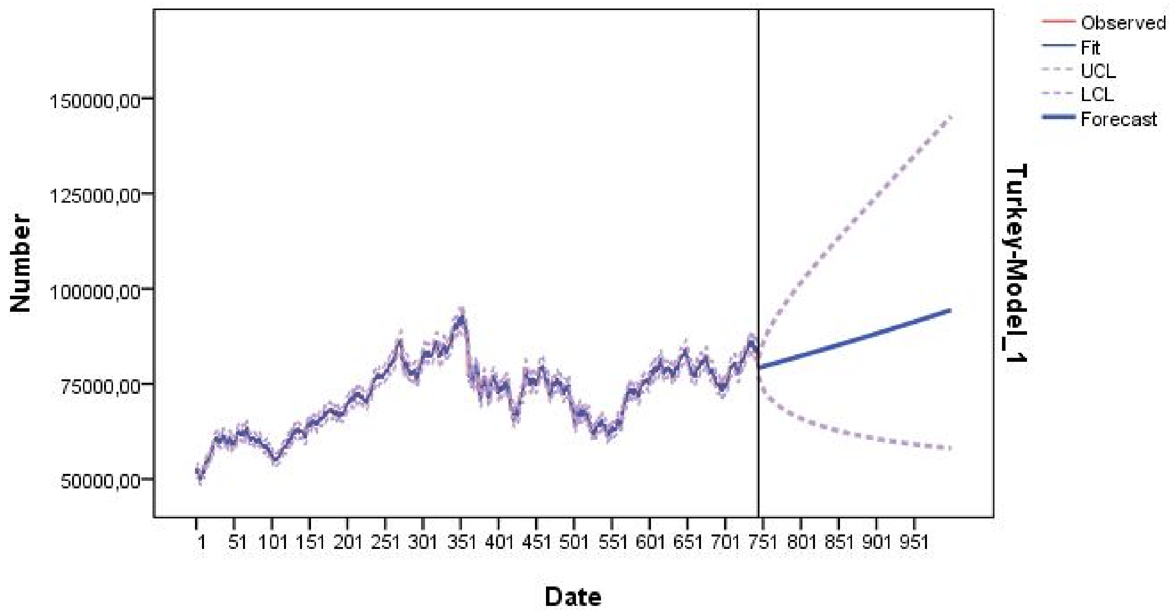


Figure 5: Prospective Forecast Graph of Turkey's ARIMA Model

755 observations were used in the model created for Turkey. Based on this model, it is forecasted that XU100 index will have an upward trend. It is seen in the Figure 5 that the index will increase from 75,000 to 90,000 in the forecasted period. In addition, the daily index closing values forecasted for the 90-day period between 01/01/2015 and 31/3/2015 were compared with the actual closing values. The model was seen to have an accuracy rate of 72.61%.

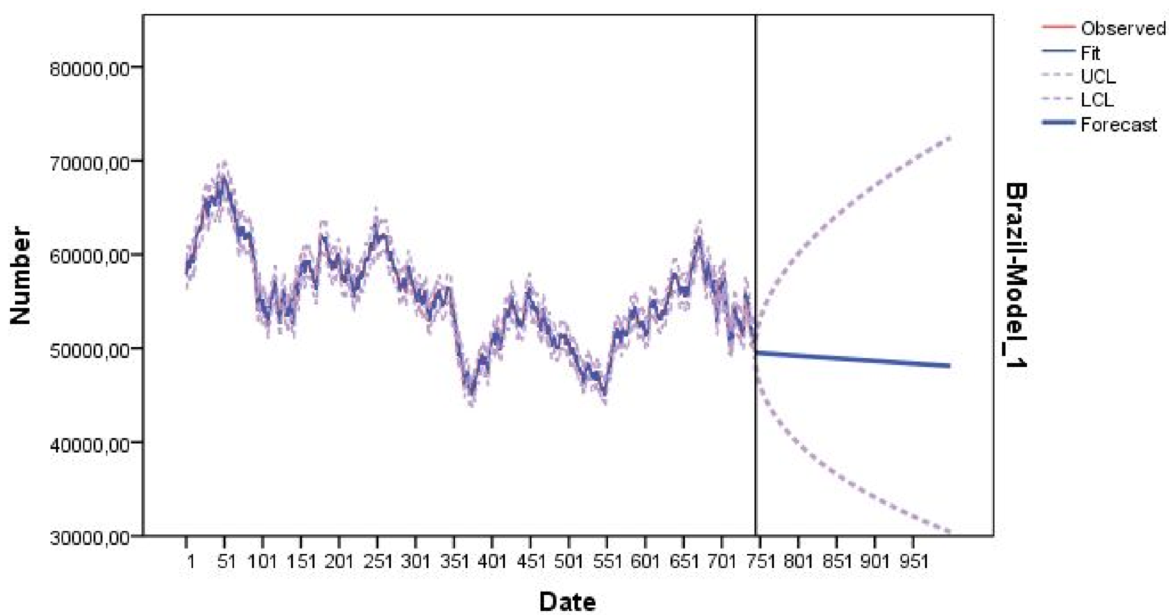


Figure 6: Prospective Forecast Graph of Brazil's ARIMA Model

759 observations were used in the model created for Brazil. Based on this model, it is forecasted that BVSP index will have a slightly downward trend. It is seen in the Figure 6 that the index will decrease from 50,000 to approximately 47,000 in the forecasted period. In addition, the daily index closing values forecasted for the 90-day period between 01/01/2015 and 31/3/2015 were compared with the actual closing values. The model was seen to have an accuracy rate of 65.48%.

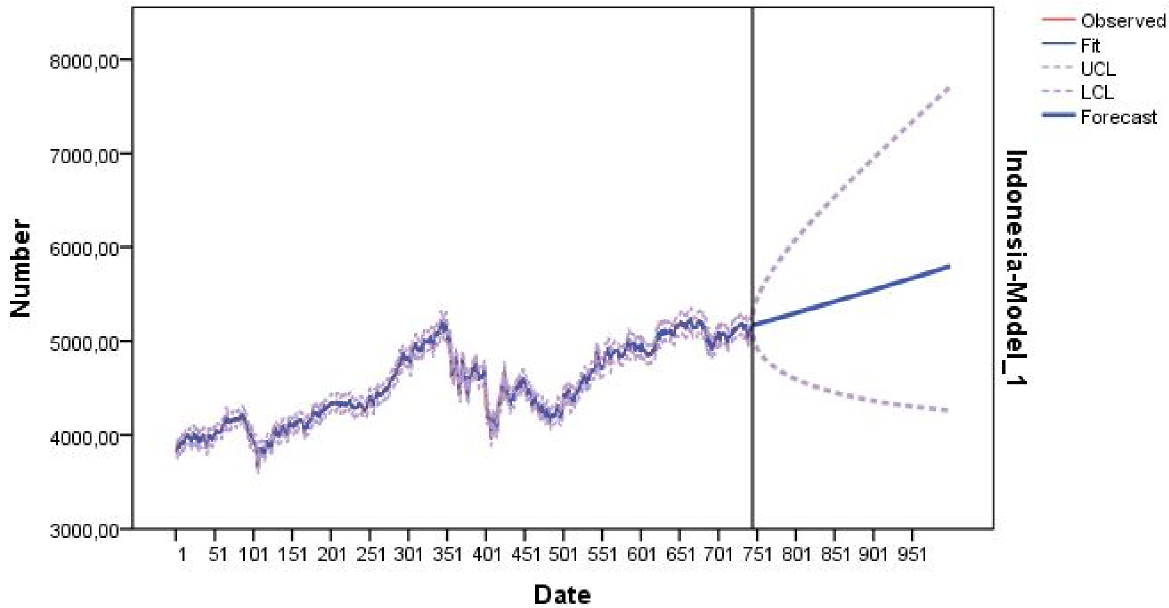


Figure 7: Prospective Forecast Graph of Indonesia's ARIMA Model

746 observations were used in the model created for Indonesia. Based on this model, it is forecasted that IDX index will have an upward trend. It is seen in the Figure 7 that the index will increase from 5,000 to approximately 5,800 in the forecasted period. In addition, the daily index closing values forecasted for the 90-day period between 01/01/2015 and 31/3/2015 were compared with the actual closing values. The model was seen to have an accuracy rate of 74.29%.

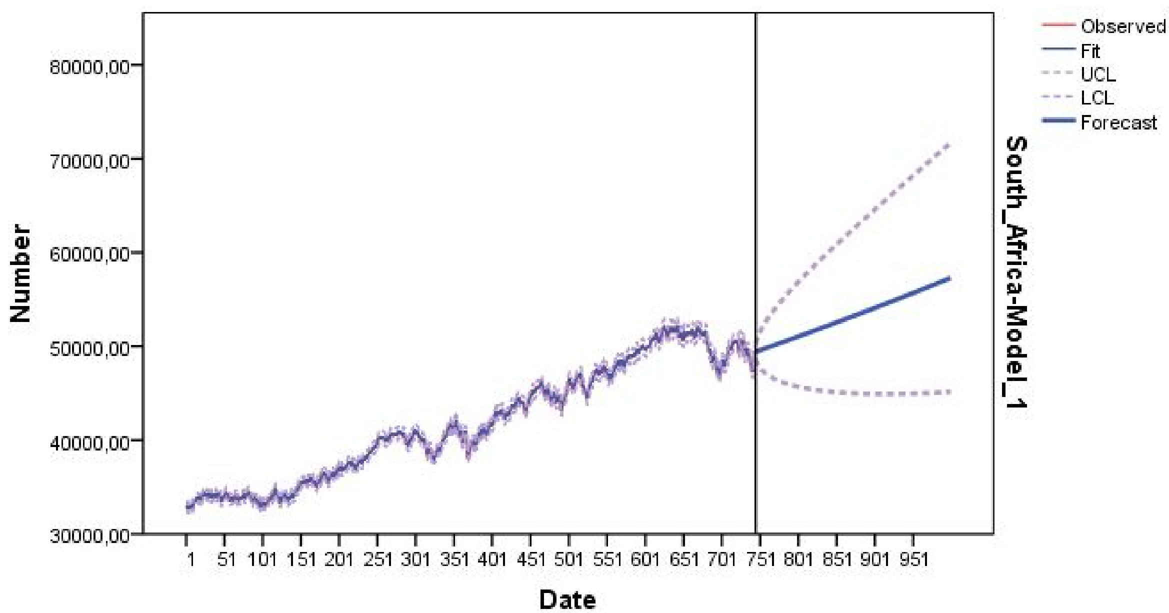


Figure 8: Prospective Forecast Graph of South Africa's ARIMA Model

749 observations were used in the model created for South Africa. Based on this model, it is forecasted that JTOPI index will have an upward trend. It is seen in the Figure 8 that the index will increase from 50,000 to approximately 60,000 in the forecasted period. In addition, the daily index closing values forecasted for the 90-day period between 01/01/2015 and 31/3/2015 were compared with the actual closing values. The model was seen to have an accuracy rate of 66.73%.

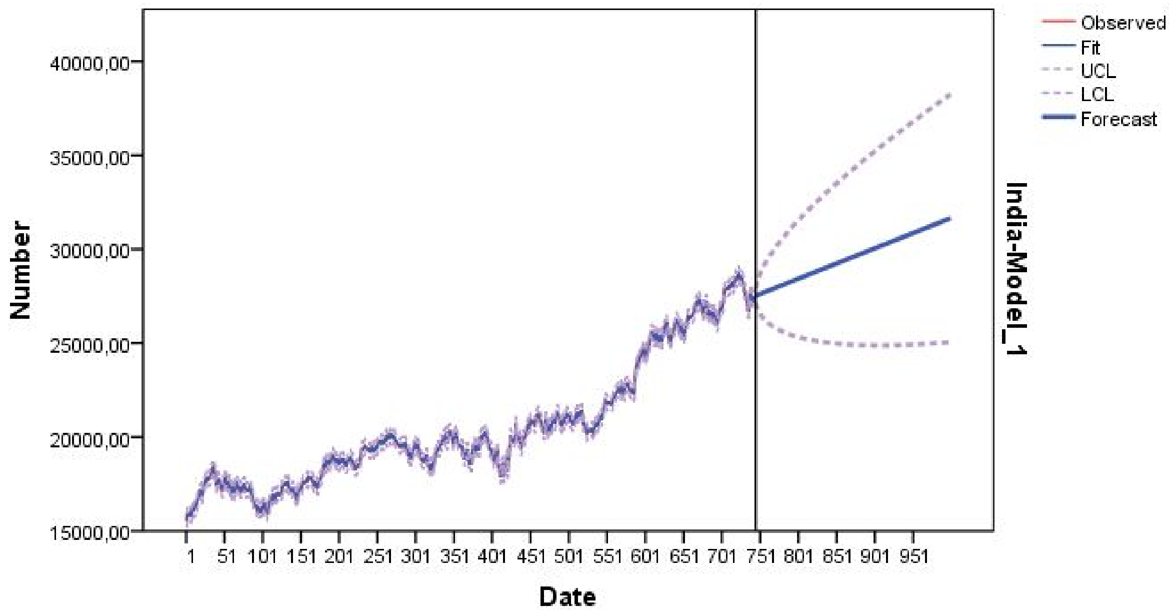


Figure 9: Prospective Forecast Graph of India's ARIMA Model

744 observations were used in the model created for India. Based on this model, it is forecasted that BSESN index will have an upward trend. It is seen in the Figure 9 that the index will increase from 27,000 to approximately 33,000 in the forecasted period. In addition, the daily index closing values forecasted for the 90-day period between 01/01/2015 and 31/3/2015 were compared with the actual closing values. The model was seen to have an accuracy rate of 59.47%.

4. Conclusion

Based on the findings obtained in this study, ARIMA models were determined for Turkey, Brazil, Indonesia, South Africa, and India, and the results were found to be quite significant. The models were also seen to have quite low error rates. The closing data obtained through the created forecasting models were compared with the actual closing data for 90 days. The findings demonstrate that the model created for Turkey forecasted with an accuracy rate of approximately 72%; that created for Brazil forecasted with an accuracy rate of approximately 65%; that created for Indonesia forecasted with an accuracy rate of approximately 74%; that created for South Africa forecasted with an accuracy rate of approximately 66%; and that created for India forecasted with an accuracy rate of approximately 59%.Since the data used for creating the models are daily and the data used for the models cover 3 years, it is normal that the models forecast the closing prices of the indexes at the above-mentioned accuracy rates.

Another reason for low accuracy rates is the volatility of relevant stock indexes. As 3-year data were used in the analysis, coefficient of variation was calculated by calculating the standard deviation of the aggregate data and dividing it by the daily average of the aggregate data. The obtained values were assumed to represent the volatility of the indexes. Volatility was found to be approximately 12% for Turkey, approximately 9% for Brazil; approximately 9% for Indonesia, approximately 14% for South Africa, and lastly approximately 16% for India. These results indicate that the forecasting models created for South Africa and India which have a higher volatility have lower accuracy rates while the forecasting models created for Turkey and Indonesia which have a lower volatility have higher accuracy rates. However, though Brazil has low volatility, the forecasting model crated for it has a low accuracy rate. The findings obtained through the analysis show that the prospective forecast of the stock index of Brazil, which is one of the fragile five countries, indicates a direction contrary to the directions of the stock indexes of other 4 countries in the same group. That shows that, as stated in the report of Morgan Stanley, most of the fragile five countries move similarly. The findings also demonstrate that, as argued in the report of Morgan Stanley, the stock indexes of the fragile five countries have similar trends to a large extent.

When the results obtained in this study are compared with the results of other studies in literature, it is seen that the models in the present study were quite good in forecasting though daily data were used. Tayyar and Tekin (2013) forecasted the direction of index based on weekly data through support vector machines method with an accuracy rate of 70%. Similarly, Demirci et al. (2011) forecasted the direction of index based on monthly data though support vector machines with an accuracy rate of 86%. Altay and Saltman forecasted with an accuracy rate of 57% by use of the model based on daily data. Diler (2003) created a forecasting model through artificial neural networks method by using daily data and forecasted the next-day situation of the index with an accuracy rate of 60%. Similarly, Boyacıoğlu and Avcı (2010) used monthly data and forecasted the monthly return of the index through artificial neural networks method with an accuracy rate of 98.3%.When the results obtained in the studies in literature are compared with the results of the present study, it is seen that the accuracy rates of the forecasting values obtained through ARIMA model used in the present study were much higher than those of the values obtained in other studies although daily data were used in the present study. If week and monthly data are used in the forecasting models employed in the present study, these models may forecast with higher accuracy rates. Moreover, predictions with higher accuracy rates may be made if the hybrid model composed of ARIMA and support vector machines models recommended by Pai and Lin (2005) and the hybrid model composed of ARIMA and artificial neural networks models recommended by Zhang (2003) are used. For that reason, the collective use of different models by researchers in future works may contribute to literature.

References

Akel, V. (2015).Analysis of Cointegration among the Stock Exchanges of Fragile Five Countries. International Journal of Management, Economics, and Business, 11(24).

Aksoy, A. (1991). Stock Indexes – Their Meaning and Importance to Investors. Gazi University Journal of Economics and Administrative Sciences.Volume 7. Issue 1-2. P. 249-271

Aktan, B., Mandaci, P. E., Kopurlu, B. S., & Ersener, B. (2009). Behaviour of emerging stock markets in the global financial meltdown: Evidence from Bric-a. African Journal of Business Management, 3(7), 396–404.

Altay, E., &Satman, M. H. (2005). Stock market forecasting: artificial neural network and linear regression comparison in an emerging market. Journal of financial management and analysis, 18.

Armano, G., Marchesi, M., & Murru, A. (2005). A hybrid genetic-neural architecture for stock indexes forecasting. Information Sciences, 170(1), 3-33.

Avcı, E., & Çinko, M. (2008). Forecasting the index returns with artificial neural network models: an application in the emerging European stock markets. The Journal of Economy, Business, and Finance, 23(266), 114-137.

Avcı, E., & Çinko, M. (2008).Forecasting the Index Returns with Artificial Neural Network Models: An Application in the Emerging European stock markets. The Journal of Economy, Business, and Finance, 23(266), 114-137.

Aygören, H., Saritaş, H., &Morali, T. (2012). Forecasting ISE 100 Indice Using Artificial Neural Networks And Newton Numerical Search Models. International Journal of Alanya Faculty of Business, 4(1).

Box G.E.P, Jenkins G., (1976). Time Series Analysis, Forecasting and Control, San Francisco: Holden-Day.

Boyacioglu, M. A., & Avci, D. (2010). An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. Expert Systems with Applications, 37(12), 7908-7912.

Bozoklu, Ş., &Saydam, İ. M. (2010). Analysing Capital Market Integration with Parametric and Nonparametric Cointegration Tests among BRIC Countries and Turkey. Maliye Dergisi (Journal of Finance). 159, 416–431.

Chen, A. S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. Computers & Operations Research, 30(6), 901-923.

Demirci, E., Özdemir, A. K., & Tolun, S. (2011). Predicting the Directıon of Stock Index Return Movement Using Binary Classification Method: An Application on the Ise-100 Index. Niğde University Journal of Faculty of Economics and Administrative Sciences, 4(2), 45.

Diler, A. İ. (2003).Forecasting the Direction of ISE National-100 Index through Artificial Neural Networks Error Back-propagation Method.ISE Review. Year 7, Issue 25- 26.65-82.

Işığıçok, E., (1993). Causality Tests in Search of Relationships between Variables and an Application Testing. Unpublished Doctoral Thesis. Uludağ University Institute of Social Sciences. Bursa

Karan, M., B., (2001). Investment Analysis and Portfolio Management. Gazi Kitabevi. Ankara

Pai, P. F., & Lin, C. S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. Omega, 33(6), 497-505.

Schwert G.W. (2002-2008). Time Series Analysis: Trend & Seasonality. APS 425 - Advanced Managerial Data Analysis.

Tayyar, N., & Tekin, S. (2013). Forecasting ISE-100 Index Using Support Vector Machines with Daily, Weekly, and Monthly Data. AbantIzzet Baysal University Journal of Social Sciences.

Tekindal, M. A., Modeling the Stock Indexes of the European Union Countries and Turkey and Evaluating Forecasts for the Future, Proceedings of 17th Statistics Research Symposium of Turk Stat, Page 135-153, May 2008.

Tosunoglu, N. G., & Benlı, Y. K. (2012). Forecasting of Morgan Stanley Capital International Turkey Index with Artificial Neural Networks. Ege Academic Review, 12(4), 541-547.

Yaman, K., Sarucan, A., Atak, M., Aktürk, N., (2001).Preparation of Data for Dynamic Scheduling Using Image Processıng and ARIMA Models. Journal of the Faculty of Engineering and Architecture of Gazi University.16(1). 19-40

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, 159-175.