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Evaluation of Stochastic and ANN Model for Karachi Stock Exchange Prices Prediction

Azhar Ali Marri[1,2*], Mir Ghulam Hyder Talpur[1]

[1] *Department of Statistics University of Sindh Jamshoro, PAKISTAN.*

[2] *Department of Statistics University of Balochistan Quetta, PAKISTAN.*

[*]*Corresponding Author (Tel: +923342432321, Email: marriazhar4@gmail.com).*

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Abstract

This study employs the linear and non-linear time series models (ARIMA) and (ANN) for Karachi stock exchange prices prediction. Further that the comparison between two-time series models was examined in this study. The results indicated that the capability of the ARIMA model is appropriate for short-term prediction and the ANN model is applicable for forecasting the future price towards value prediction. This study results demonstrated that the pattern of the ARIMA model was directional towards stock market prices prediction and the ANN model was towards value prediction.

Disciplinary: Financial Mathematics, Financial Market & Stock Trading.

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1 Introduction

Stock market forecasting is a common goal of investors and researchers. The stock market provides a platform to investors where they can buy and sell shares. An accurate movement of stock prices prediction may produce profits for investors (Jayasuriya & Dulani 2017). The stock market is an equity market and is a place where publically held companies are traded and issued securities, bonds, shares over exchanges or over-the-counter markets (Korir 2018). According to recent literature stock market is dynamic, complex in nature and practically has a non-linear pattern of time series data (Hiransha, et al. 2018). Time series is a set of observations observed at a specific time to obtain the status of some activity (Coskun, et al. 2009). There is a wider range of time series forecasting techniques and approaches used to obtain accurate predictions (Ayasuriya & Dulani 2017). Estimating an efficient model for the stock market data analysis and forecasting of stock market prices is a very difficult task due to its complexity in nature. Box & Jenkins et al. (1970) developed an ARMA/ARIMA model. This model is a more popular modeling technique mostly used for investigation and forecasting of a linear pattern of the dataset and is in exercise for decades (Wang, et al. 2012; Pandey and Bajpai 2019). ARIMA model is a traditional modeling technique its uses are wide for stock market forecasting (Almasarweh and Wadi 2018; C. Wang 2011). ANN model has demonstrated its potential to capture the non-linear pattern of the dataset and has attracted the overwhelming attention of researchers for time series modeling and forecasting (Wang, et al. 2012; Adebiyi et al. 2014). For the past several years, ANN modeling for stock exchange forecasting is in practice (Hiransha, et al. 2018). Stock exchange historical data prediction using the ANN model produced significantly more accurate results than the traditional linear and non-linear prediction models (Chiang, et al. 2007; Pandey and Bajpai 2019).

Karachi stock exchange (KSE) is the oldest and biggest stock market of Pakistan, established on the 18th of September 1947. Its first index was introduced in 1991 as the KSE-50 share index and established with top 50 companies on open and cry structure. Currently, KSE has four indexes known as; (i) KSE 100- Index (ii) KSE all-share index (iii) KSE-30 share index, and (iv) KMI-30 index. We used KSE 100 Index dataset in this study.

This study's objective is to investigate and compare the forecasting accuracy of two-time series models ARMA/ARIMA and ANN models using the KSE 100-Index dataset.

2 Literature Review

Several research studies have been conducted on the estimation, modeling, and forecasting of stock market prices with different solution techniques proposed by various authors over the years. Wang et al. (2012) stated forecasting procedures fall into two broad classes (i) Statistical computing techniques and (ii) Soft computing techniques. Statistical computing procedure comprised of several techniques like as exponential smoothing technique, autoregressive integrated moving average (ARIMA) model, and generalized autoregressive conditional heteroskedasticity (GARCH) volatility model (Adebiyi et al. 2014; Wang et al. 2012; Franses and Ghijsels 1999). Box & Jenkins (1970) introduced an ARMA/ARIMA model which undertakes the future values of the variable should be in a linear form based on past several variables. ARMA/ARIMA model was constructed with three parametric components comprised of autoregressive (AR), integration (I) and moving average (MA) components). ARMA/ARIMA has commonly used as an efficient technique for forecasting social sciences and is most extensively used for time serimodelinging (Adebiyi et al. 2014). Tabachnick et al. (2001) and Zhang (2003) reported probabilistic evaluation and forecasting of the ARMA/ARIMA model is essential because these techniques do not assume the underlying knowledge as some other techniques practice. Meyler et al. (1998) stated ARMA/ARIMA model often surpassed the most sophisticated models in relation to its short-short-runshiplling ability.

Some preceding literature concentrated on forecasting stock exchange returns with artificial intelligence techniques. The most intelligent technique used for financial market forecasting is the artificial neural network (ANN) technique. Zhang et al. (2005) reported ANN model identifies the hidden practical relationships in the dataset perfectly. Jayasuriya & Dulani (2017) testified different types of ANN models and found these models have acceptably predicted the stock exchange returns and its movement direction. Dase & Pawar (2010) described ANN techniques applied most frequently for stock market prediction and as the most efficient and faster technique than the other forecasting techniques for larger datasets prediction. White (1989) stated ANN is generally a functional approximator and draws conclusions accurately to any nonlinear form of a dataset. White (1989) defined ANN are universal function approximators and can plot any non-linear function. Masters (1993) identified ANN as a powerful technique for pattern recognization classification and forecasting and is less sensitive to the error term assumption. Furthermore, the advantages of ANN modeling are better for fault tolerance. Its robustness and flexibility are linked with the expert systems for a large number of the interrelated processing components and allow improvements for new patterns (Lipman 1987; Trippi & Turban 1992).

Lee et al. (2007) compared the performance of the NN and SARIMA model using (KOSPI) Korean stock exchange data and found the NN model performed well. Yao et al. (1999) investigated the performance of the ANN and ARIMA model using Kuala Lumpur stock exchange data and explored ANN has better forecasting ability than the conventional statistical ARMA/ARIMA model. Wijaya et al. (2010) equated the stock exchange prediction results of ANTP (PT Aneka Tambang) an Indonesia stock exchange through ANN and ARIMA modeling and established forecasting with ANN model had smaller error than the ARIMA model.

3 Data and Methodology

The objectives of the study are estimation, modeling and comparison of prediction performance of ARMA/ARIMA and ANN model. In this study, secondary data of the KSE 100 Index comprising of the daily closing price index was used. The chosen dataset was obtained from http://finance.yahoo.com for a period of 01-01-1990 to 31-12-2019. The dataset consists of 7241 daily observations. The tool used in the study was R software version 3.6.2.

3.1 ARMA/ARIMA Model

Box & Jenkins (1976) introduced an ARMA/ARIMA model. This model is also discussed as the Box-Jenkins technique consists of a set of actions that identify, estimate and diagnose the time series data. The Box-Jenkins methodology ARMA/ARIMA model is the most conspicuous technique of the study in financial time series prediction (Pie & Lim 2005; Merh et al. 2010; Nochai & Titida 2006). Box-Jenkins ARMA/ARIMA model has efficient capability in producing short term predictions for nonlinear time series datasets and constantly overtook the structure of complex models for short term prediction (Meyler et al. 1998). Box-Jenkins ARMA/ARIMA model generates the future values of a variable is to be a linear combination of historical prices and previous errors terms displayed as follows.

$$Y_r = \emptyset_0 + \emptyset_1 Y_{r-1} + \emptyset_2 Y_{r-2} + \cdots + \emptyset_p Y_{r-p} + \varepsilon_r - \theta_1 Y_{r-1} - \theta_2 Y_{r-2} - \cdots - \theta_q Y_{r-q} .. \quad (1),$$

where Y_r represents actual values random error term of r time is ε_r, $\emptyset_i$, θ_j are the coefficients of the model and p, q are integers that are often referred to as auto regressive and moving averages terms for the model respectively.

The ARMA/ARIMA model is constructed as a predictive model and consists of three steps identification of the model, estimation of the parameter, and diagnostic checking (Tabachnick et al. 2001). We used in this study auto-arima functions of the R software version 3.6.2 to select the best ARMA/ARIMA model order and analyzed the residuals of the selected model with the Ljung Box test.

3.2 Artificial Neural Network Model

The knowledge of neural networks was introduced by human beings' nervous system which contains a number of simple processing units called neurons (Jayasuriya & Dulani 2017; Naeini et al. 2010). ANN model is a nonlinear type of modeling technique and is generally used to examine the nonlinear pattern of the dataset (Zhang 2003). Recent literature has exposed single hidden layer feed-forward neural network model is used most extensively for time series modeling (Zhang et al. 1998). ANN model is a machine learning technique to make decisions and attempts to mimic the system of learning from the working of the human brain for making decisions (Tsay 2010). Its function mimics biological neurons whose structure comprises a group of artificial neurons and are interlinked with the developed networks. The basics of the neuron for learning the system are inputs, Weight, Summation Functions, Transformation function and output. Similar to the human brain the process of networks is required to differentiate between the patterns for improvement, generalization and to learn the system towards increasing the performance. Therefore the ANN is a powerful tool to explain the problems it has an appropriate capacity of estimation, forecasting and classification. Mathematically ANN model can be written as

$$y_t = f(y, w) + \varepsilon .. \quad (2),$$

where y is the explanatory variable, w is a vector for weight parameter and ε is the component for random error. Following equation (4) is used for the estimation and prediction of unknown functions from the available data.

Our study considered three layers' neural network model through simple processing units and associated with the acyclic links. Mathematically the relation between output values (y_t) and the inputs values ($y_{t-1}, y_{t-2}, \cdots, y_{t-p}$) are presented as

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}) + \varepsilon_t \ldots \quad (3),$$

α_j (j= 0,1,2,....,q), β_{ij} (i = 0,1,2,....,p, j= 1,2,.....,q) are the parameters of the studied model and identified as connection weights. In-network p and q are the total number of input nodes and total no of hidden nodes. The hidden layer transformation function or sigmoid function is denoted by g(x) and written as

$$g(x) = \frac{1}{1+\exp(-x)} \qquad (4).$$

Equation (3) performs as a nonlinear function and obtains information from the historical observations found as $(y_{t-1}, y_{t-2}, \cdots, y_{t-p})$ to predict the future value denoted by y_t i.e.

$$y_t = f\big(y_{t-1,}y_{t-2}, \ldots . y_{t-p}, w\big) + \varepsilon_t \qquad (5).$$

Here w is the vector for the parameters and f is shown as the function through the network and connection weight. The ANN model is similar to a nonlinear autoregressive model. It is a powerful network and it has the ability to estimate an arbitrary function when the hidden node (q) in the network is sufficiently large in number (Hornik 1990). The simple ANN structure with the smallest number of hidden nodes mostly performed well for the prediction of out-of-training samples and may be the cause of overfitting which effect typically and found in the neural network modeling process (Zhang 2003). The overfitted model shows a good fit to the sampled data and in general, its prediction performance for out-of-training sample data is poor (Zhang 2003). The choice for hidden nodes "q" is data-dependent and there is no systematic rule for determining this type of parameter.

4 Model performance measurement

The following three methods were used to measure the forecasting performance of the study

i. Actual and forecasted values are compared with a graph of the training procedure.

ii. Comparison of statistical parameters like coefficient of determinant R^2, root mean squared error (RMSE), mean absolute error (MAE), MAPE (mean absolute percentage error), normalized mean squared error (NMSE). MAE and NMSE Equations (8) and (9) are the statistical parameters used to estimate the relationship between the actual and predicted values (Jenkins et al. 1970; Kashi & Mehdi 2010). If the results are not reliable using the abcriteriaia's then it is useful to apply MAPE equation (7) (Makridakis 1993).

iii. Prediction accuracy of ANN model for testing dataset (out of sample) was analyzed with DA (directional accuracy) equation (10) higher DA will produce better forecast (Wang, et al. 2012).

$$\text{RMSE} = \left(\frac{\sum_{r=1}^{n}(Y_r-\hat{Y}_r)^{2}}{n}\right)^{1/2} \qquad (6),$$

$$\text{MAPE} = \frac{1}{n}\sum_{r=1}^{n} |\,(Y_r - \hat{Y}_r)/Y_r| \qquad (7),$$

$$\text{MAE} = \frac{1}{n}\sum_{r=1}^{n} |\, Y_r - \hat{Y}_r| \qquad (8),$$

$$\text{NMSE} = \frac{1}{n}\sum_{r=1}^{n}\frac{(Y_r-\hat{Y}_r)^2}{\sigma^2\,\hat{Y}_r} \qquad (9),$$

$$\text{DA} = \frac{100}{n}\sum_{r=1}^{n} d_r \qquad (10),$$

where $d_r = \begin{cases} 1 = (Y_r - Y_{(r-1)})(\widehat{Y}_{(r)} - \widehat{Y}_{(r-1)}) \geq 0 \\ 0 = \quad \text{otherwise} \end{cases}$

5 Results and discussion

5.1 Box Jenkins ARIMA Model

The closing prices index was converted into logarithmic series following (Campbell and Walker 1977). The whole period of the study is divided into two parts the training dataset or in-sample for N observations estimation and testing dataset the out-of-sample or validation period for T-N observations for prediction.

Table 1: Descriptive statistics & Augmented Dickey-Fuller test

	Mean	S.D	Skewness	Kurtosis	JB	T
Logarithmic series	8.61	1.354	0.078	-1.615	586.19*	7241
Stationary series	0.00058	0.014	-0.200	9.190	11606*	7240

Augmented Ducky-Fuller (ADF) test		
Estimates Series	Logarithmic series	Stationary series
ADF test	-2.320	-16.392
Lag order	19	19
p-value	0.443	0.01

Note: JB is Jarque Bera Normality test and * denotes significance level at 5 percent level

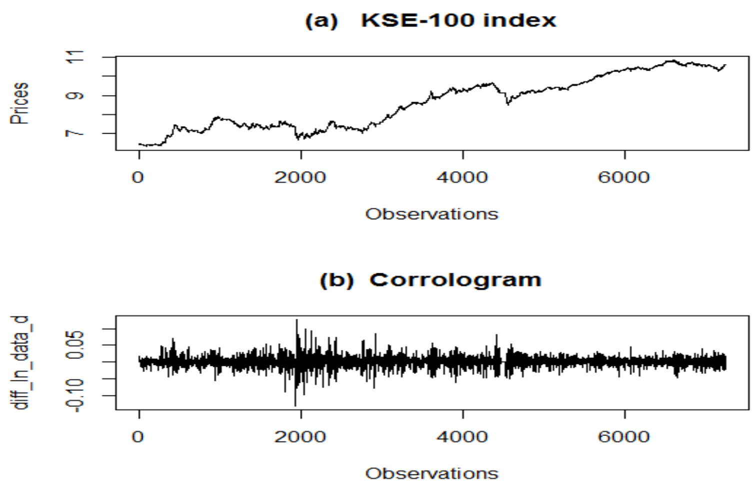

Figure 1: (a) KSE 100 index log(prices) (b) Stationary series correlogram

Table 1 displayed descriptive statistics for logarithmic and stationary series of KSE 100 index daily closing prices. Skewness and kurtosis were found at 0.078 and -1.615 respectively which showed the dataset was not stationary (Figure 1a), likewise, it was confirmed with the ADF test. After applying the first difference to the logarithmic series the series was found stationary as presented in Figure 1b and confirmed with the ADF test (Table 1). JB test rejected the null hypothesis for the presence of normality in logarithmic and stationary series (Table 1).

Table 2: Selected ARIMA order (1, 1, 2), Evaluation criteria & Error measurement

Variable	ar1	ma1		ma2	drift
Coefficients	0.894	-0.765		-0.074	0.0006
Standard error	0.031	0.033		0.014	0.0003
Diagnostic of selected ARIMA order (1,1,2) and training dataset error measurement					
AIC	BIC	RMSE	MAE		MAPE
40951.9	-40917.8	0.0141	0.0096		0.117
Evaluation criteria of the testing dataset					
Criteria	RMSE	MAE	MAPE	NMSE	DA
Coefficients	2022.355	1677.169	0.0415	1.726	6697.294

Table 3: Box-Ljung test of ARIMA order (1, 1, 2) & Correlation.

df	5	10	15	20
X-squared	0.937	8.323	8.918	21.138
p-value	0.967	0.597	0.882	0.389
Correlation between actual and Forecasted prices				
Correlation		Actual		Forecasted
Actual		1.000		0.911
Forecasted		0.911		1.000

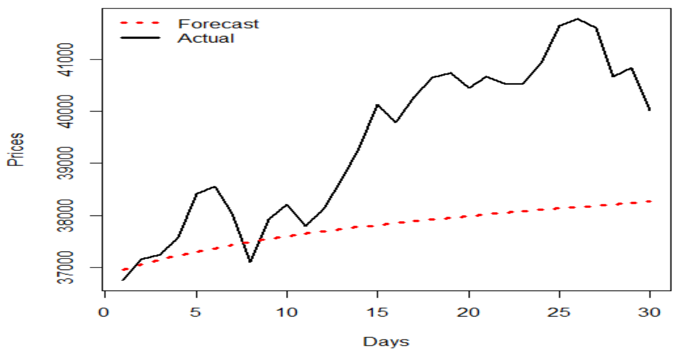

Figure 2: Actual and forecasted prices

Table 2 showed the diagnostic of selected ARIMA order (1,1,2) with standard error and drift analyzed for training dataset using smallest values of AIC (Akaike Information Criteria) and BIC (Bayesian Information Criterion). The evaluation criteria for the training dataset were obtained with the smallest values of RMSE, MAE, MAPE and testing dataset also with smallest values of RMSE, MSE, MAPE, NMSE and higher value of DA which represents the best fit of the predicted model (Table 2). Box-Ljung test of autocorrelation was applied on residuals of the forecasted model for various degrees of freedom and found not significant which disclosed there is no autocorrelation present in the residuals of forecasted model (Table 3). Next 30 days prices were predicted and compared with the actual testing data set (Figure 2). The coefficient of correlation was investigated 0.912 between the actual testing dataset and predicted values (Table 3). Analysis of the study revealed that the prediction of the ARIMA model was directional and appropriate for short-term prediction. These results were also supported by the study of Khashei & Bijari (2010); Adebiyi et al. (2014) and Pieleanu (2016).

5.2 ANN model

In the ANN modeling, 7241 observations were used in which 7211 observations were analyzed for the in-sample training period and 30 observations for of sample testing period. The training dataset error was found at 0.058 using 59728 steps (Figure 3) and estimated r^2 = 98.9 (Figure 4) similar results were also found by Anwar and Mikami, (2011).

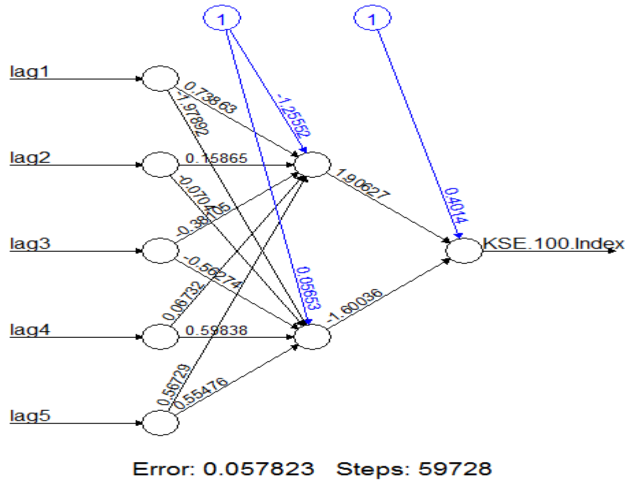

Figure 3: Neural network model with lags

Table 4: Evaluation critera & Correlation.

Variables	RMSE	MAE	MAPE	NMSE	DA
Coefficients	0.01859	0.00852	0.00853	0.12007	0.000708
Correlation between actual and forecasted prices					
Variables	Actual		Forecasted		
Actual	1.000		0.943		
Forecasted	0.943		1.000		

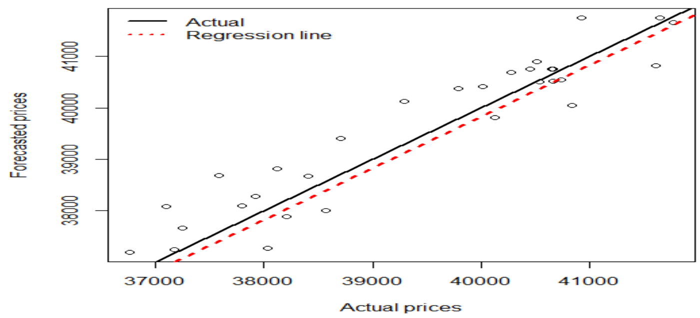

Figure 4: Regression line on the scattered plot

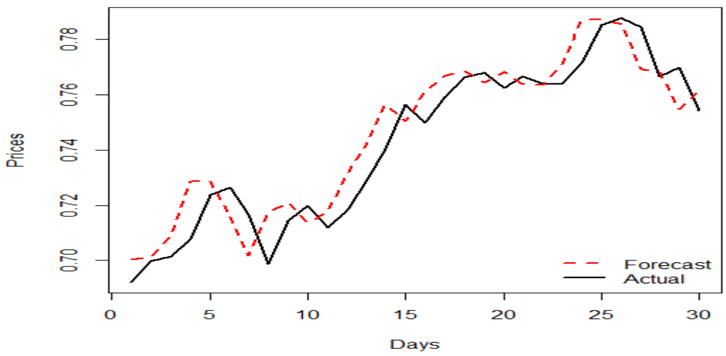

Figure 5: Actual and forecasted prices

Table 4 showed the evaluation criteria of the testing data set. The smallest values of RMSE, MAE, MAPE, NMSE and highest values of DA were selected. The coefficient of correlation for the testing data set was found 0.9432 (Table 4). In addition to that ANN model was found appropriate for value prediction for stock prices. Our findings are supported by the study of Adebiyi et al. (2014; Pandey and Bajpai (2019).

6 Conclusion

Time series modeling is a dynamic area of research over the preceding few decades. Forecasting accuracy is an important topic to many decision analysts and hence the search for improving the effectiveness of forecasting has never been stopped. In this paper, we proposed linear and non-linear time series modeling for KSE 100- Index. The empirical results of the study shown the ANN model performed better than the ARIMA model. ARIMA model performed better for short-term prediction using KSE 100-Index. Furthermore, the prediction performance of the ARIMA model was satisfactory and we can say that the performance of the ARIMA model was acceptable for the short-term prediction.

7 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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Azhar Ali Marri is an Assistant Professor at the Department of Statistics, University of Balochistan Quetta, Pakistan. He earned his M.Sc degree from Shah Abdul Latif University Khairpur Sindh, Pakistan, and M.Phil.degrees from the University of Sindh Jmshoro, Pakistan. Azhar Ali Marri is a Ph.D. scholar of the Department of Statistics, University of Sindh, Jamshoro, Pakistan. His research is related to Statistics emphasizing Operations Research and Time Series Analysis.

Professor Dr. Mir Ghulam HyderTalpur is a Professor in Statistics at the University of Sindh Jamshoro, Pakistan. He holds a B.Sc. (Hons) and M.Sc. Statistics from University of Sindh, Jamshoro and a Ph.D. degree in Operations Research from Shanghai University of Science & Technology (now renamed to “Shanghai University, Shanghai), P.R. China. Dr. Talpur did Post Doctorate at Ball State University Muncie Indiana USA. His theoretical background is Probability, Queuing Theory, Markov Decision Chains, Regression Models, Sampling Survey, Time Series Analyses, and Applied Statistics in Agriculture & Metrology.