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Comparative Study of an ANN-ARIMA Hybrid Model for Predicting Karachi Stock Price

Shafaq Ayub[1,2,*], Yasmin Zahra Jafri[1]

[1]Department of Statistics, University of Balochistan, Quetta, Pakistan
[2]Agriculture Research Institute, Quetta, Pakista

Abstract Autoregressive Integrated Moving Average (ARIMA) has been considered a popular linear model for forecasting time series. Artificial Neural Network (ANN) has been considered a powerful tool which is used to define the complex economic relationships with various patterns. In this study, the forecasting performance of Hybrid ANN-ARIMA is compared with Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) of KSE viz. National Foods (NATF) and Engro Foods (EFOOD). Experimental results obtained show the excellence of Hybrid NN-ARIMA model over ANN and ARIMA, respectively. Further, it can be concluded that Hybrid ANN-ARIMA model has the best forecasting accuracy for forecasting stock price.

Keywords Time Series forecasting, Artificial Neural Network, ARIMA model, Zhang's Hybrid model

1. Introduction

A stock market defined as collection of buyers and sellers of stocks. Stock market is an essential part in country's economy. Karachi Stock Exchange (KSE) is oldest stock exchange of Pakistan. KSE is considered to be one of the best performing markets of Asia. Time series forecasting is very important in the research field over many years due to its various applications. Stock price prediction is one of the most popular issues in economics and finance which has motivated the researchers to develop better predictive model over the years. Time series data has increasing or decreasing trends having different characteristics. Statistical predicting models are used to develop forecasting methodology by using the data to predict stock values with the help to identify the trends of data.

ARIMA (Box and Jenkins) as statistical technique is widely used for forecasting and analysis of time series data in different fields as social sciences, engineering, finance and agriculture [1]. ARIMA model is considered to be an efficient model in financial time series forecasting. ARIMA model has been explored in many literatures for better prediction of stationary time series data. ARIMA models represent different kinds of time series as AR, MA and ARMA series [2]. ARIMA models are flexible in nature and have powerful and efficient capability than other structural models to generate short run stock price forecasting [3].

Artificial Neural Network (ANN) a soft computing technique commonly used for forecasting time series with a high point of accuracy in different fields as social sciences, industry, business, finance and stock problems [3]. ANN performance is better than ARIMA when data show maximum volatility and multicollinearity. ANN is efficient for solving nonlinear real world problems; therefore it is not required to make data stationary. In this paper, the performance of ARIMA and ANN for stock prices forecasting is being compared and it further clarifies the superiority of each of the following models over one another. ANN model provided effective results as compare to ARIMA.

The combination of different models or Hybrid models have been frequently used for better stock price prediction by manipulating the unique strength of each of the models [4]. A combination of ANN and ARIMA provide more precise predicting model for forecasting time series data as compared to an individual model [14]. The results being obtained from all datasets clarify that Hybrid model has higher prediction accuracy for one-step and multi-step ahead forecasts and a various number of NN models and Hybrid models have been used for obtaining accurate prediction [16-17]. In this paper, Hybrid model is developed by using unique modeling techniques of ARIMA and ANN for better forecasting performance and the performance of Hybrid model is contrasted with ANN and ARIMA.

* Corresponding author:
shafaqayub321@gmail.com (Shafaq Ayub)
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2. Literature Review

In this literature, the search for the productive stock price forecasting methods is studied for the sake of better results. Buyuksahin et al. [1] presented ARIMA –ANN Hybrid method that works in a more general structure and study revealed that ARIMA provides better forecasting accuracy with stationary data while ANN is more suitable for non-stationary data. The empirical results obtained from ARIMA indicated that ARIMA models are suitable to predict stock prices on short term forecasting. Zhang et al. [2] defined that Hybrid methodology of model is proposed to take advantage of unique strength of ANN and ARIMA in nonlinear and linear modeling respectively. Results showed that combined model has improved forecasting accuracy as compared to model are used individually. Adebiyi et al. [3] worked in comparison of the forecasting performance of ANN and ARIMA for forecasting New York Stock Exchange time series data. The study revealed that both models can achieve good forecasted results for stock price prediction. Merh et al. [5] worked to develop Hybrid models of ARIMA and ANN for forecasting future stock price index of Indian stock market viz. SENSEX, BSE Oil & Gas, BSE IT, S&P CNX Nifty and BSE 100. The results showed that work of Hybrid ANN-ARIMA better than Hybrid ARIMA-ANN. Xiong; L. et al. [6] introduced Hybrid ARIMA-BPNN for predicting the stock price of Chinese stock market. Hybrid ARIMA-BPNN model to forecast time series data of Chinese Stock Index, BPNN defines nonlinear structure and ARIMA defines linear structure and future values are predicted. Prybutok et al. [7] contrasted forecasting work of ARIMA, regression and ANN in predicting ozone concentration. The finding showed ANN provided better performance as compared to regression and ARIMA. The work reported in [9] compared the performance of ANN and ARIMA in forecasting Korean Stock Index. ARIMA provided more reliable forecasts as compared to BPNN model. Wijaya et al. [10] showed a comparison between ANN model and ARIMA model based on Indonesia Stock Exchange and results showed ANN provided better performance than ARIMA model. Khashei et al. [12] compared the work of ARIMA-MLP and MLP-ARIMA models for predicting Stock index. The results showed MLP-ARIMA Hybrid model provided better results than ARIMA-MLP. Tang et al. [13] discussed the results of a comparative study of the work of ANN and ARIMA for forecasting time series. The results proved that NN is better in the long term forecasting while Box-Jenkins model is better for short term forecasting. Babu et al. [14] explored ARIMA and ANN to tool a new Hybrid model for better prediction of time series. The results defined that Hybrid model which combines power of ANN and ARIMA is better than individual models. Wang et al. [15] presented Hybrid model combining ARIMA, ESM and BPNN for predicting Stock Index. The results of work reported in [19-20] indicated that Hybrid models improve the accuracy of ANFIS and ARIMA for time series forecasting. Taskaya-Temizel et al. [23] combined ARIMA and TDNNs models to form hybrid model to forecast nine real data sets. The results defined that Hybrid models don't always perform well as model selection process plays an important role in the popularity of Hybrid models. Zhou et al. [24] suggested Hybrid model based on ARIMA model and Grey to predict gyro drift. It is concluded Hybrid method has a higher forecasting accuracy to real problems than single method.

This paper further clarifies the conflicting views reported in literature reviews about the excellence of ANN over ARIMA in forecasting stock prices and Hybrid model to improve forecasting accuracy of time series by using unique strengths of ARIMA and ANN. The experimental results obtained are built on the study of stock price forecasting using data from KSE.

3. Research Methodology

3.1. Data Collection

Data used in this research work is daily stock prices of two different products of Food and Personal care named National Foods and Engro Foods listed in KSE. Stock data included open, low, high and close prices of National Foods and Engro Foods. In this paper, close price is selected to be predicted and modeled as closing price defines every activity of stock price index of whole day. Matlab R2014a and Eviews9 are used for simulation of ANN model and ARIMA model, respectively. The data is taken from *www.kse.pk.com.*

3.2. Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive Integrated Moving Average (ARIMA) is considered to be a powerful model that is applied to time series data. ARIMA models are based on three parameters i.e. autoregressive (p), moving average (q) and first differencing (d) of the time series. First, time series is transformed into stationary by differencing and suitable ARMA model is fitted to the series.

General form of ARMA model is written as follows:

$$\hat{Y}_t = \mu + \theta_1 Y_{t-1} + \dots + \theta_p Y_{t-p} - \varphi_1 e_{t-1} - \dots - \varphi_q e_{t-q} \quad (1)$$

The suitable ARIMA model for stock price index can be constructed by determining AR and MA parameters and the value of d can be determined as total number of differencing performed on data. The best ARIMA model is determined according to criterion as follows:

- Relatively small BIC
- Relatively small SER
- Maximum adjusted R^2
- Q-statistics and Correlogram revealed that no significant pattern left at ACF and PACF of residuals.

3.2.1. ARIMA (p, d, q) Model for National Foods (NATF) Stock Price

NATF data is taken from the period 1st January, 2015 to 30th April, 2019 having total number of 1019 observations. The initial pattern of National Foods is illustrated in Figure 1 to review whether given series is stationary or not.

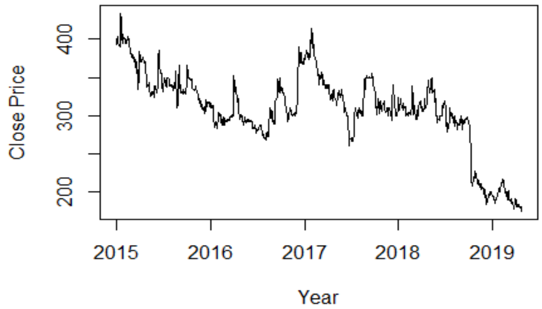

Figure 1. Graphical representation of NATF closing price index

Correlogram is used to direct whether a given series is stationary or nonstationary. Since ACF dies out gently with time which means the pattern of NATF price index is nonstationary because it has random walk patterns. Figure 2 shows a graph of NATF after differencing.

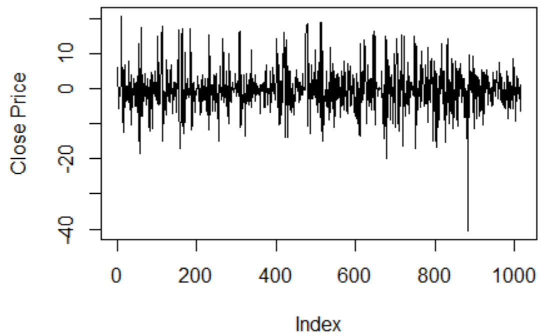

Figure 2. Graphical representation of NATF stock index after differencing

Nonstationary data of NATF becomes stationary after first differencing.

3.2.2. ARIMA (p, d, q) Model for Engro Foods (EFOODs) Stock Price

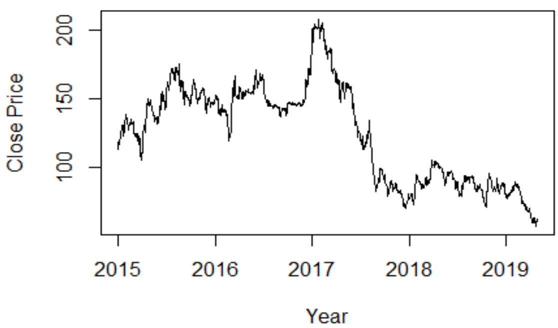

Figure 3. Graphical representation of EFOOD closing price index

EFOOD data used in this study was taken from the period 1st January, 2015 to 30th April, 2019 having total no of 1077 observations. Figure 3 illustrates the pattern of EFOODs time series and series is found to be nonstationary.

The nonstationary time series data is converted into stationary by differencing. For the sake to build the best ARIMA model for Engro Foods stock index, AR and MA parameters are determined effectively according to above criteria. Figure 4 shows a graph of EFOODs after differencing.

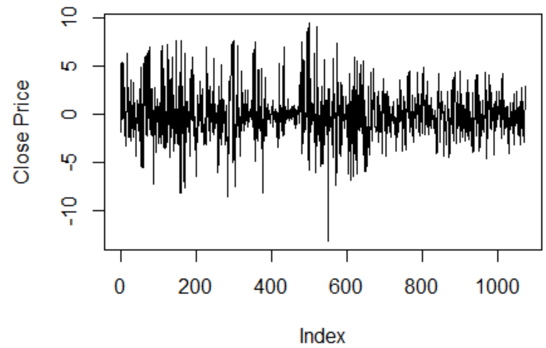

Figure 4. Graphical representation of EFOODs stock index after differencing

Engro Foods stock index reshaped to stationary after first difference.

3.3. Artificial Neural Network Model

NN is set of artificial neurons, perceptrons, nodes and groups of processing units that process and transfer information through activation functions. ANN is widely used for estimating the model and prediction. ANN is a nonlinear network and it is suited for prediction purpose because it doesn't make assumptions. NNs model is referred for various predictive data mining applications because of its power, adaptability and a high level of accuracy. Multilayer perceptron (MLP) is most commonly used for forecasting time series. MLP network has input, output and hidden layer [18] and the nodes of one layer are linked with the nodes of the following layer to send information. The link between i and j nodes of the following layers is attached with a weight ω_{ij}.

For the sake to choose best training algorithm for ANN model, several empirical results are made by changing the number of hidden nodes and layers with various training algorithms. The accuracy of NN can be increased by increasing the size of a number of layers and nodes. [1]

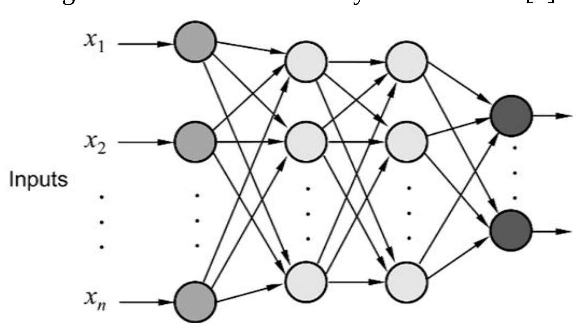

Figure 5. Multilayer Feed Forward Neural Network

3.3.1. Artificial Neural Network Model for National Foods (NATF)

This study utilized a three-layer MLP model trained with back propagation algorithm. Open, high, low and close price of NATF time series data is taken to construct ANN. The constructive model of ANN involves input neurons, hidden layers with number of hidden neurons and output neurons. For the sake to establish predictive model, the data is normalized having a range between 0 and 1 by using the formula:

$$x_{ni} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Where x_{ni} is the normalized value, x_i is the real stock value and x_{max} and x_{min} are maximum and minimum values of data. NN predicted values which are in range (0, 1) being changed into real stock values by the respective formula:

$$x_i = x_{ni}(x_{max} - x_{min}) + x_{min} \quad (3)$$

In favor to train neural network, Feed-forward backpropagation is used as network type. We chose open, high, low price as an input data and close price is taken as a target data, TRAINGDM is taken as training function, LEARNGDM taken as adaptation learning function, transfer function (TANSIG) and MSE is chosen as performance function. Further, the training parameters are put as lr = 0.01, mu = 0.9 and data is being instructed with 1000, 2000 and 5000 epochs with different ANN structures.

Table 1. Statistical performance of ANN of NATF

Network Structure	MSE		
	1000 Epochs	**2000 Epochs**	**5000 Epochs**
10-10-1	0.00207	0.00169	0.00138
10-11-1	0.00769	0.00405	0.00169
10-12-1	0.00153	0.00106	0.000636
10-13-1	0.00371	0.00246	0.00102
10-14-1	0.00252	0.00192	0.00145
10-15-1	0.00132	0.00105	0.000793
10-16-1	**0.000986**	**0.000722**	**0.000523**
10-17-1	0.00144	0.00103	0.000584
10-18-1	0.0015	0.00122	0.000875

Table 1 shows the performance of different NN structures in various training periods of NATF that defines the prediction accuracy of various models. In the above table bold figures indicated the best results among various epochs. The network structure having least MSE in each of the models is evaluated to be the best model.

3.3.2. Artificial Neural Network Model for Engro Foods (EFOODs)

MLP model contains three layers that are used to utilize EFOOD time series data. Open, high, low and close price of EFOOD is taken to construct ANN.

For sake to train feed-forward backpropagation is used as network type. Open, high, low price taken as input data and close price is taken as a target data, TRAINGDM as training function, LEARNGDM as adaptation learning function, TANSIG is taken as transfer function and performance function MSE. The training parameters are set as lr = 0.01, mu = 0.9 and data is instructed with 1000, 2000 and 5000 epochs with different ANN structures.

Table 2. Statistical performance of ANN of EFOOD

Network Structure	MSE		
	1000 Epochs	**2000 Epochs**	**5000 Epochs**
10-10-1	0.0078	0.0035	0.0017
10-11-1	0.0095	0.0054	0.0027
10-12-1	**0.0008**	**0.0007**	**0.0006**
10-13-1	0.0094	0.0026	0.0012
10-14-1	0.0091	0.0039	0.0018
10-15-1	0.0079	0.0032	0.0018
10-16-1	0.0054	0.0035	0.0008
10-17-1	0.0060	0.0029	0.0015
10-18-1	0.0084	0.0047	0.0013

Table 2 represents the performance of different NN structures in various periods of Engro Foods. In the above table bold figures indicated the best results among various epochs. NN having minimum MSE is desired network for given time series.

3.4. Hybrid Model

Zhang presented Hybrid ARIMA-ANN model [1, 15] to get more precise results as compared to using ARIMA and ANN individually. Hybrid techniques are used to divide time series data into its linear and nonlinear shape [1]. Various Hybrid techniques have been used for many years to take advantage of the unique strengths of each various types of models in real life data sets. The purpose of combining the models is due to the assumption that a single model can't define all the characteristics of time series [12]. Hybrid ANN-ARIMA technique is proposed by Zhang [1,15] and Khashei et al. [1,24] that define the relationship between two components. Time series y_t can be defined as:

$$y_t = L_t + N_t \quad (4)$$

L_t and N_t are linear and nonlinear components respectively. At First, ANN is used to give the nonlinear forecasts and residuals from nonlinear components are considered to have linear link. Let e_t denotes the residuals from ANN model thus:

$$e_t = y_t - \hat{N}_t \quad (5)$$

Where $\hat{N}_t$ is the predicted values of ANN model. Secondly, ARIMA model forecasts linear component then the results are combined together to improve the performance of models. The new time series can be defined as:

$$\hat{y}_t = \hat{N}_t + \hat{L}_{t'} \quad (6)$$

Where $\hat{L}_t'$ is forecasted value from ARIMA model based on the residual data.

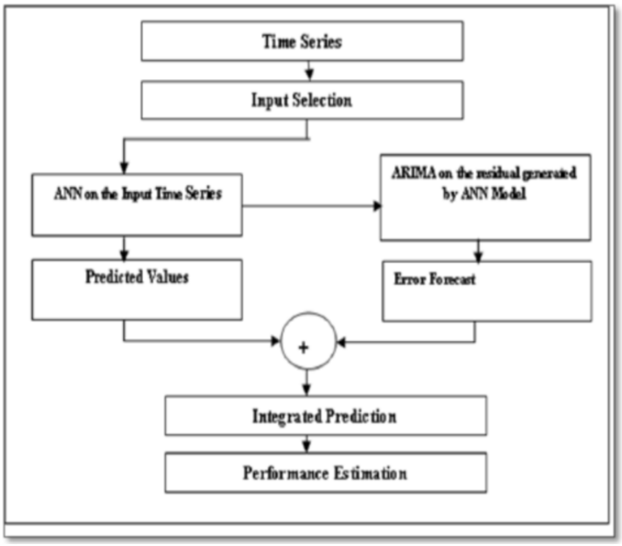

Figure 6. Hybrid ANN-ARIMA Flow Chart

4. Results and Discussion

MatlabR2014a and Eviews9 are used for simulation of ANN and ARIMA, respectively. The experimental results are being obtained is described below:

4.1. Results of ARIMA Models

4.1.1. Result of ARIMA Model for National Foods Stock Price Prediction

ARIMA (1, 1, 3) is considered to be the best model for National Foods (NATF) to give the best forecast values having least BIC of 6.4724 and smallest SER of 6.0837. The best model showed as follows:

$$Y_t = \theta_1 Y_{t-1} - \varphi_1 e_{t-1} - \varphi_2 e_{t-2} - \varphi_3 e_{t-3} + \varepsilon_t \quad (7)$$

Where ε_t is a residual.

Table 3. Statistical results of different ARIMA parameters for NATF

ARIMA	BIC	Adjusted R^2	SER
(1, 1, 1)	6.4809	0.0137	6.1098
(1, 0, 1)	6.4869	0.9866	6.1139
(1, 1, 0)	6.4746	0.0142	6.1084
(3, 1, 3)	6.4880	0.0067	6.1313
(3, 1, 1)	6.4744	0.0201	6.0900
(1, 1, 3)	**6.4724**	**0.0221**	**6.0837**

The actual and forecasted values are shown in Table 4 where bold figures indicated the best results of ARIMA model of NATF. Figure 7 gives a graphical representation of forecasted price against actual price to look at the presentation of ARIMA model being selected. The results are found satisfactory.

Table 4. Experimental Results of ARIMA of NATF Stock Index

Sample Period	Actual Values	Predicted Values
01-03-2018	313.000	304.000
02-03-2018	310.010	303.798
05-03-2018	305.100	303.680
06-03-2018	299.000	303.563
07-03-2018	298.990	303.466
08-03-2018	297.250	303.328
09-03-2018	295.340	303.211
12-03-2018	295.000	302.976
13-03-2018	300.000	302.589
14-03-2018	306.960	302.741
15-03-2018	301.500	302.624
16-03-2018	299.000	302.506
19-03-2018	302.000	302.390
20-03-2018	312.850	302.272
21-03-2018	314.170	302.150
22-03-2018	317.470	302.037
26-03-2018	320.000	301.919
27-03-2018	320.000	301.802
28-03-2018	315.000	301.685
29-03-2018	315.000	301.567
30-03-2018	310.000	301.450

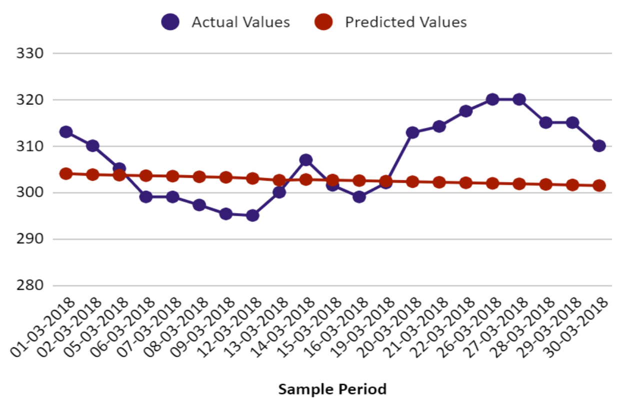

Figure 7. Graph of actual stock prices vs predicted stock prices of NATF using ARIMA

4.1.2. Result of ARIMA Model for Engro Foods Stock Price Prediction

ARIMA (1, 1, 1) is found to be best model for Engro Foods according to above-mentioned criteria with BIC of 4.8167 and smallest SER of 2.6599. The best model showed as follows:

$$Y_t = \theta_1 Y_{t-1} - \varphi_1 e_{t-1} + \varepsilon_t \quad (8)$$

Where $\varepsilon_t = Y_t - \hat{Y}_t$

Table 5. Statistical results of different ARIMA parameters for EFOOD

ARIMA	BIC	Adjusted R^2	SER
(1, 1, 1)	**4.8167**	**0.0129**	**2.6599**
(1, 0, 1)	4.8207	0.9944	2.6587
(1, 0, 0)	4.8298	0.9943	2.6783
(0, 0, 1)	8.7141	0.7263	18.7018

The actual and forecasted values are shown in Table 6 where bold figures indicated the best results of ARIMA model of EFOOD. Figure 8 gives a graphical representation of forecasted price against actual price to look at presentation of ARIMA model being selected. The results are found satisfactory.

Table 6. Experimental Results of ARIMA of EFOOD Stock Index

Sample Period	Actual Values	Predicted Values
01-03-2018	92.120	80.864
02-03-2018	92.250	80.856
05-03-2018	92.900	80.848
06-03-2018	92.990	80.840
07-03-2018	91.160	80.832
08-03-2018	89.690	80.824
09-03-2018	87.510	80.816
12-03-2018	88.430	80.808
13-03-2018	88.680	80.800
14-03-2018	90.760	80.793
15-03-2018	91.100	80.786
16-03-2018	89.170	80.777
19-03-2018	89.180	80.769
20-03-2018	93.380	80.760
21-03-2018	96.460	80.753
22-03-2018	97.370	80.745
26-03-2018	102.230	80.737
27-03-2018	105.730	80.729
28-03-2018	105.350	80.721
29-03-2018	103.310	80.712
30-03-2018	102.040	80.705

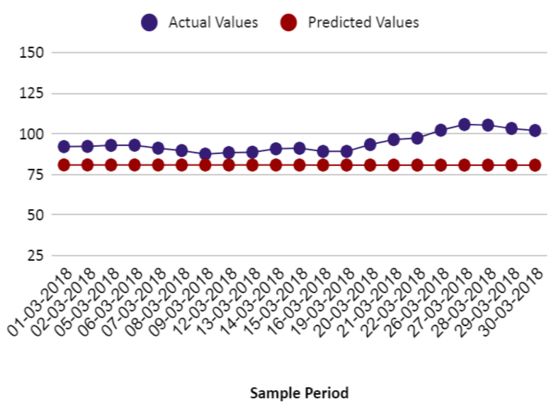

Figure 8. Graph of actual stock prices vs predicted stock prices of EFOOD using ARIMA

4.2. Results of ANN Models

4.2.1. Result of ANN Model for National Foods Stock Price Prediction

Many experiments of various network architecture based on ANN are performed. The network structure with smallest MSE was considered to give the best prediction results. It was noticed that 10-16-1 (10 inputs, 16 hidden neurons in hidden layers and 1 output) is best forecasted model of daily price prediction with a high level of accuracy. The results of ANN are presented in Table 7 and Figure 9 is a graphical representation of ANN model of actual values against forecasted values for National Foods.

Table 7. Experimental Results of ANN of NATF Stock Index

Sample Period	Actual Values	Predicted Values
01-03-2018	313.00	313.139
02-03-2018	310.01	311.839
05-03-2018	305.10	307.976
06-03-2018	299.00	306.620
07-03-2018	298.99	301.174
08-03-2018	297.25	300.339
09-03-2018	295.34	299.161
12-03-2018	295.00	298.868
13-03-2018	300.00	303.270
14-03-2018	306.96	306.101
15-03-2018	301.50	307.167
16-03-2018	299.00	302.892
19-03-2018	302.00	305.367
20-03-2018	312.85	310.872
21-03-2018	314.17	315.046
22-03-2018	317.47	316.187
26-03-2018	320.00	321.539
27-03-2018	320.00	319.171
28-03-2018	315.00	315.544
29-03-2018	315.00	315.858
30-03-2018	310.00	311.858

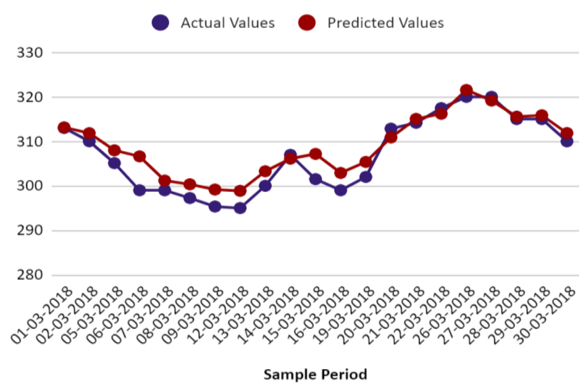

Figure 9. Graph of actual stock prices vs predicted stock prices of NATF using ANN

4.2.2. Result of ANN Model for Engro Foods Stock Price Prediction

Many experiments of various network architecture based on ANN are performed. It was noticed that 10-12-1 (10 inputs, 12 hidden neurons in hidden layers and 1 output) is best forecasted model of daily Efood stock price prediction with a high level of accuracy. The results of ANN model are presented in Table 8 and Figure 10 is a graphical representation of ANN of actual values against forecasted values for Engro Foods stock index.

Table 8. Experimental Results of ANN of EFOOD Stock Index

Sample Period	Actual Values	Predicted Values
01-03-2018	92.120	86.390
02-03-2018	92.250	90.770
05-03-2018	92.900	89.680
06-03-2018	92.990	90.220
07-03-2018	91.160	89.610
08-03-2018	89.690	87.740
09-03-2018	87.510	86.790
12-03-2018	88.430	86.100
13-03-2018	88.680	86.250
14-03-2018	90.760	90.220
15-03-2018	91.100	89.110
16-03-2018	89.170	87.380
19-03-2018	89.180	86.710
20-03-2018	93.380	88.750
21-03-2018	96.460	92.40
22-03-2018	97.370	82.575
26-03-2018	102.230	94.930
27-03-2018	105.730	105.500
28-03-2018	105.350	105.040
29-03-2018	103.310	104.470
30-03-2018	102.040	101.850

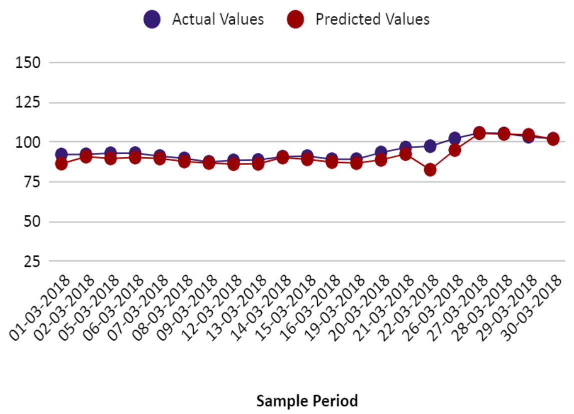

Figure 10. Graph of actual stock prices vs predicted stock prices of EFOOD using ANN

4.3. Hybrid ANN-ARIMA Model Results

4.3.1. Hybrid Model for Forecasting National Food (NATF)

There are two steps to build Hybrid ANN-ARIMA model for forecasting NATF as follows:

In first step, ANN is used to predict close price of NATF and residuals e_t is produced and provided to ARIMA to predict error. In second step, the predicted close price by ANN is summed with error produced by ARIMA model to give the final predicted values.

Where $e_t = Y_t - N_t$, Y_t is time series while N_t is the nonlinear component. ARIMA is used to reproduce e_t to generate forecast series of NATF. Table 9 defines the performance of Hybrid ANN-ARIMA verses ANN and ARIMA and Figure 11 defines graphical representation of Hybrid model of NATF against ANN and ARIMA.

Table 9. Experimental Results of Hybrid Model of NATF Stock Index

Sample Period	Actual Values	ARIMA	ANN	Hybrid
01-03-2018	313.00	304.000	313.139	313.562
02-03-2018	310.01	303.798	311.839	310.753
05-03-2018	305.10	303.680	307.976	305.821
06-03-2018	299.00	303.563	306.620	299.765
07-03-2018	298.99	303.466	301.174	299.765
08-03-2018	297.25	303.328	300.339	297.972
09-03-2018	295.34	303.211	299.161	295.893
12-03-2018	295.00	302.976	298.868	295.597
13-03-2018	300.00	302.589	303.270	300.665
14-03-2018	306.96	302.741	306.101	307.661
15-03-2018	301.50	302.624	307.167	302.173
16-03-2018	299.00	302.506	302.892	299.765
19-03-2018	302.00	302.390	305.367	302.778
20-03-2018	312.85	302.272	310.872	313.562
21-03-2018	314.17	302.150	315.046	314.819
22-03-2018	317.47	302.037	316.187	318.301
26-03-2018	320.00	301.919	321.539	320.537
27-03-2018	320.00	301.802	319.171	320.537
28-03-2018	315.00	301.685	315.544	315.765
29-03-2018	315.00	301.567	315.858	315.765
30-03-2018	310.00	301.450	311.858	310.753

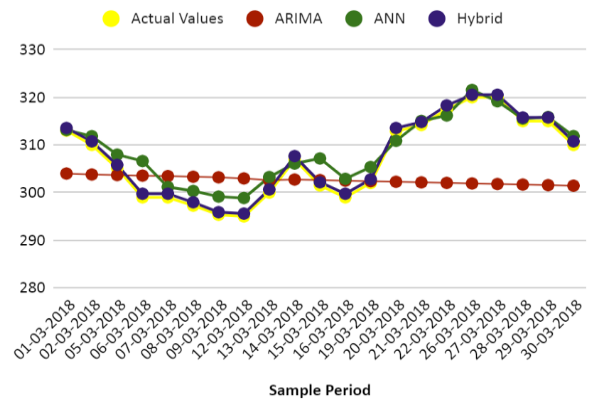

Figure 11. Graph of actual stock prices vs predicted stock prices of NATF using Hybrid model

4.3.2. Hybrid Model for Forecasting Engro Foods (EFOODs)

Hybrid ANN-ARIMA model to forecast EFOOD consists of following two steps:

In first step, ANN is used to predict close price of EFOOD then the residuals e_t being produced are provided to ARIMA to predict the error. In second step, the predicted close price by ANN is summed with error produced by ARIMA to give the final predicted values.

Table 10. Experimental Results of Hybrid Model of EFOOD Stock Index

Sample Period	Actual Values	ARIMA	ANN	Hybrid
01-03-2018	92.12	80.864	86.39	87.686
02-03-2018	92.25	80.856	90.77	92.922
05-03-2018	92.90	80.848	89.68	91.227
06-03-2018	92.99	80.840	90.22	91.861
07-03-2018	91.16	80.832	89.61	91.783
08-03-2018	89.69	80.824	87.74	89.693
09-03-2018	87.51	80.816	86.59	89.667
12-03-2018	88.43	80.808	86.10	87.926
13-03-2018	88.68	80.800	86.25	88.062
14-03-2018	90.76	80.793	87.73	89.389
15-03-2018	91.10	80.786	89.11	91.137
16-03-2018	89.17	80.777	87.38	89.547
19-03-2018	89.18	80.769	86.71	88.562
20-03-2018	93.38	80.760	88.75	90.219
21-03-2018	96.46	80.753	92.40	93.942
22-03-2018	97.37	80.745	94.67	96.488
26-03-2018	102.23	80.737	94.93	96.239
27-03-2018	105.73	80.729	105.5	116.350
28-03-2018	105.35	80.721	105.0	113.640
29-03-2018	103.31	80.712	104.4	103.433
30-03-2018	102.04	80.705	101.8	102.460

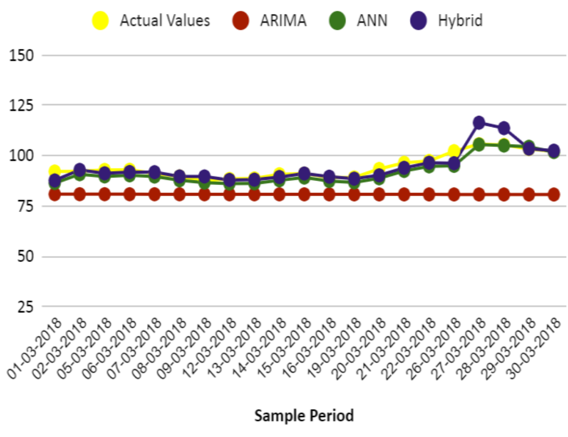

Figure 12. Graph of actual stock prices vs predicted stock prices of EFOOD using Hybrid model

Where $e_t = Y_t - N_t$, Y_t is time series while N_t is the nonlinear component. ARIMA is used to reproduce e_t to generate forecasted series of EFOOD. Table 10 defines the performance of Hybrid ANN-ARIMA verses ANN and ARIMA and Figure 12 defines graphical representation of Hybrid model of EFOOD against ANN and ARIMA.

5. Conclusions

In this paper, the experimental results are being obtained by using ARIMA, ANN and Hybrid ANN-ARIMA for predicting NATF and EFOOD stock prices index. The performance of Hybrid model is compared with Artificial Neural Network (ANN) and ARIMA. ANN is applied to identify the nonlinear structure of data while ARIMA model is used to identify the linear structure of data. We also observed that ANN provided better results as compared to ARIMA where the pattern of ARIMA models is directional. In further studies, Hybrid ANN-ARIMA model achieved good forecasted values as compared to ARIMA and ANN. The work also clarified the contradictory theory reported in literature about the excellence of Hybrid model over ANN and ARIMA.

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