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Forecasting using Artificial Neural Network and Statistics Models

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Abstract

Forecasting is very important for planning and decision-making in all fields to predict the conditions and cases surrounding the problem under study before making any decision. Hence, many forecasting methods have been developed to produce accurate predicted values. Consumer price indices provide appropriate and timely information about prices changes, which affect the economy of all Yemenis because of their different uses in many ways. It can be used as an economic indicator (wider use in the inflation measurement), and as a means of regulating income. It is also used as a supplement for statistical chains to predict future value indices in order to make sure that the data accurately reflect the patterns purchased by the Yemeni consumer. In this paper, we propose a modified artificial neural network method to predict the indices of consumer in the Republic of Yemen to the prices of the period from 01/01/2005 till 01/01/2014. The results of using the proposed method is compared to a classical statistical method. The proposed method is based on artificial neural networks, namely, back propagation with adaptive slope and momentum parameter to update weights. However, the statistical method is Box-Jenkins model which is used to predict time series. The experimental results show that artificial neural networks gives better predictive values due to their ability to deal with the nonlinear and stochastic data better than traditional statistical modeling techniques.

Index Terms: Forecasting, Time series models, Neural networks, Box-Jenkins, Consumer price index, Back propagation, Adaptive slope, Momentum parameter.

1. Introduction

Prediction of time-series is one of the critical areas where there is much use of applications of Artificial Neural Networks (ANNs) as an alternative or equal method to the traditional statistical methods which are used in the prediction of time-series such as moving-average, exponential smoothing Box-Jenkins models[1]. These traditional methods are known in general as time series analysis methods. The neural networks models have competed the traditional forecasting methods used in the prediction and even gave better accuracy results in

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many cases [1, 2]. Researchers have been interested in the development of various methods for the purpose of forecasting using neural networks as one of the newest used methods. It is still ongoing research in this area to investigate the effectiveness of this method. Most neural networks; which allow learning from experience and past experiments to infer new ones, are used as tools to analyze the data for the same areas covered by traditional statistical methods. Neural networks give a suitable way to represent relationships between variables which are different from the traditional methods and considered as modern statistical tools. The forecasting process analyzes the data prior to the phenomenon being studied to identify the general pattern of this phenomenon in the future. This is one of the basic operations of the neural networks, i.e. patterns identification and analysis.

Neural networks are non-linear flexible functions that do not require the availability of restrictive assumptions about the relationship between the dependent and the independent variables. In addition to their accuracy when used on parametric data, neural networks can be used for nonparametric or small-sized data. What distinguishes networks models is the lack of any assumptions or preconditions when applied in the field of forecasting as in the statistical methods that some assumptions should be fulfilled before applying them. For example, in Box Jenkins models the assumption of stability must be fulfilled before constructing the model. This assumption is not required during constructing the networks models. There are many successful applications of neural networks in various areas, such as medicine, engineering, banks, insurance and other business practices, and they are considered as important tools to investors for the prediction of investment behavior and choosing the best investment alternatives. The use of neural networks to predict the time-series began at the end of the eighties and the first attempt was in [3, 4, 5], who used the perceptron multilayer and the back propagation algorithm in the prediction of unstable time series. In [6], the authors introduced a study that supports the use of neural networks in the prediction of time-series and explains the use of the back propagation algorithm to train the network. This study has given better results when compared to many of the traditional statistical methods as Regressive Linear or Box-Jenkins.

Consumer Price Index(CPI) is defined as the average of the changeable consumer prices for their daily life requirements. These prices are collected every month to get equal time periods to calculate the rate of change in these prices increase. The inflation amount is calculated using statistical methods, The results of these data affect the economic change in the consumer and society in the Republic of Yemen [7]. predicting the prices, the network is provided with the change in the price and the stored quantity and all the financial and marketing indicators to get an output of this network for the expected price of this item in the future.

In the current study, we compare between two methods; forecasting techniques in time series and artificial neural networks models. The first method is the traditional statistical models, such as Box- Jenkins models. It is an attractive approach in time series analysis as it provides us with a comprehensive statistical modeling methodology and covers a wide variety of styles ranging from stability, the lack of stability, as well as the seasonal time series [8,9]. The second method is based on Back propagation neural networks with adaptive slope and momentum parameter to update weights. learning from experience and past experiences to derive new experiences and experiments. It is considered as one of the methods of artificial intelligence, in general, and machine learning, in particular. Most neural networks are used as tools for data analysis for the same areas covered by traditional statistical methods. Neural networks provide an appropriate representation of relationships between variables which are different way from traditional methods and seen as modern statistical tools [1]. Moreover, neural networks are suitable for identifying the linear and nonlinear characteristics presented in the time series data.

The rest of this paper is organized as follows; Section 2 contains a brief literature review of the related work. Section 3 presents the methodology used to conduct this study. In section 4, the experimental results are presented and discussed. Finally, the conclusion of this study is given in Section 5.

2. Related Work

There are many studies that preceded this study in using statistical methods, as well as artificial neural networks that focused on the prediction of time-series In [8], Elias presented a neural networks model and compared the generated predictions with those obtained from the method of Box-Jenkins for analysis and modeling of time series of the flow of water entering the City of Mosul for the period (1950-1995). The researcher concluded that the Box Jenkins method was more convenient than those given by the method of neural networks.

Another study was done by [10], that study presented the development of standard models to predict the numbers of students expected to join the first level of the primary schools until 2015, using the methodology of Box-Jenkins, the best model of Autoregressive Integrated Moving Average(ARIMA) and Autoregressive Moving Average(ARMA) models. The study concluded that the best model among the models that were developed in that research was the model ARIMA (0.1.1).

A comparison between the three methods (ARIMA) which models Buckeyes Jenkins, Pattern Modeling Recognition System (PMRS), as well as ANNs. These three methods and applied to the data of the Iraqi market for securities of the year 2006. The results showed superiority of ANN through a standard error used [11].

A comparison of direct and iterative artificial neural network forecast approaches in multi-periodic time series forecasting in application was utilized in [12]. The researchers found that using the direct method was better than the iterative method and the forecasting results with ANN were better than the other methods. Multilayer Perceptron (MLP) neural network was used for predicting the maximum and minimum temperature. They used the data of 60 years (1901-1960) for training and tested their method by forecasting the maximum and minimum temperature for over 40 years after the period whose data is used for training. The results based on Mean Square Error (MSE) confirms that using MLP is successful for weather forecasting.

One of the most recent studies in the topic was published by [13]. This paper presented a comparison between using linear models and nonlinear approaches based on the forecasting performance. Pre-processed official statistical data of overnight stays and tourist arrivals from all over the world to Catalonia from 2001 to 2009 was used in the study. The experimental results were obtained for different time horizons using each technique. These results showed that ARMA models outperform self-exciting threshold auto regressions and artificial neural network models, especially for shorter horizons. This study suggested that there was a trade-off between the pre-processing degree and the forecasting accuracy when using the neural networks, which were more suitable for the nonlinear data.

In [14], four different interval ARIMA-base time series methods were used for financial markets forecasting. The used methods are: Fuzzy Auto-Regressive Integrated Moving Average (FARIMA), Fuzzy Artificial Neural Network (FANN), ARIMA and Hybrid Fuzzy Auto-Regressive Integrated Moving Average (FARIMAH). The reported experimental results showed that the FANN model is better than other models. The prediction of the time series data in [15] was performed using ARIMA(1.1.1) model and ANN models like MLP, Functional-Link Artificial Neural Network (FLANN) and Legendre Polynomial Equation (LPE). The results obtained using all ANN models were very accurate for complex time series model.

3. Methodology

This section presents the methodology adopted for conducting this study. It gives a description of the techniques that were used in this research and explains how they were employed to achieve the objectives of this method. In this section, the used statistical model and the proposed ANN are presented.

3.1. Statistical Model

The first model used in this study is based on the Box-Jenkins method supported by [16]. This model is based on a set of stages:

- Identifying the appropriate model from the family of ARIMA models.
- Estimation model.

- Model checking to verify the suitability of the series-under study- and when it is not appropriate we go back to the first phase, otherwise move on to the next phase.
- Prediction using the chosen model.

The models proposed by Box and Jenkins to represent the stable time series of the second order are:

3.1.1. Moving Average Processes: MA(q)

Assuming that $\{u_t | t \in T\}$ is the White Noise Process at a rate of zero and variance σ_v^2 then the process $\{X_t | t \in T\}$ is said to be moving averages process of rank q, referred as the symbol MA (q) and formed as [17, 18]:

$$x_t = u_t + \alpha_1 u_{t-1} + \alpha_2 u_{t-2} + \ldots + \alpha_q u_{t-q} \qquad ; t \in T \tag{1}$$

3.1.2. Autoregressive Processes: AR (p)

Assuming that $\{u_t | t \in T\}$ is the White Noise Process at a rate of zero and variance σ_v^2 then the process $\{X_t | t \in T\}$ is said to be autoregressive process of rank p, referred as the symbol AR (p) and formed as [17,18].

$$x_t = \beta_1 u_{t-1} + \beta_2 u_{t-2} + \ldots + \beta_q u_{t-q} + u_t \tag{2}$$

Where {βi} represents Autoregressive Parameters.

3.1.3. Mixed Autoregressive Moving Average Models ARMA (p. q)

The usefulness from time-series is the ability to integrate autoregressive AR and moving averages MA process. In this model, the ARMA contains p of the terms of autoregressive process, and q of the terms of the moving averages process. This model referred to as ARMA (p, q), and written as follows [10, 18]:

$$x_t = \beta_1 u_{t-1} + \beta_2 u_{t-2} + \ldots + \beta_q u_{t-q} + u_t - \alpha_1 u_{t-1} + \alpha_2 u_{t-2} + \ldots + \alpha_q u_{t-q} \tag{3}$$

Most of the time series is unstable series, and the Secular Trend is a component of these series. In this case either the normal difference or the seasonal difference must be taken or both, to achieve stability. The general model in the case of taking the normal difference, is referred to ARIMA denoted as ARIMA (p, d, q) [18][19].

3.2. Artificial Neural Networks

The neural networks approach is one of the most important fields of Artificial Intelligence (AI), which is a modern science used in a lot of modern and complex applications, such as robotics industry systems, decision support systems, automated control systems, and identification and prediction systems.

ANN approach is an efficient forecasting tool [20]. This method consists of algorithms that mimic the features of brain of human being. These features are generating and exploring new knowledge by learning [21, 22]. ANN consists of some elements that should be determined carefully because they effect the methods' forecasting performance. The essential elements that determine the ANN are [6]: Architecture structure and learning algorithm. The architecture is determined by deciding the number of layers and number of neurons nodes in each layer [24] and there is no general rule for determining the best architecture [23]. The links that connect the neurons of a layer to the neurons of another layer are called weights. These weights are determined by a learning algorithm that updates their values.

Feed-forward back propagation network is one of the most neural networks architectures that is used widely for forecasting due to its simple usage and success [25, 26]. The multilayer feed forward ANN consists of three parts: input, hidden, and output layers as shown in Fig. 1 Each layer consists of neurons and stating the neurons number in each layer determines the architecture structure. Back Propagation algorithm is one of the most used learning algorithms which updates the weights based on the difference between the output value of the ANN and the desired real value. In the forecasting, the inputs are the past observations and the output is the predicted value.

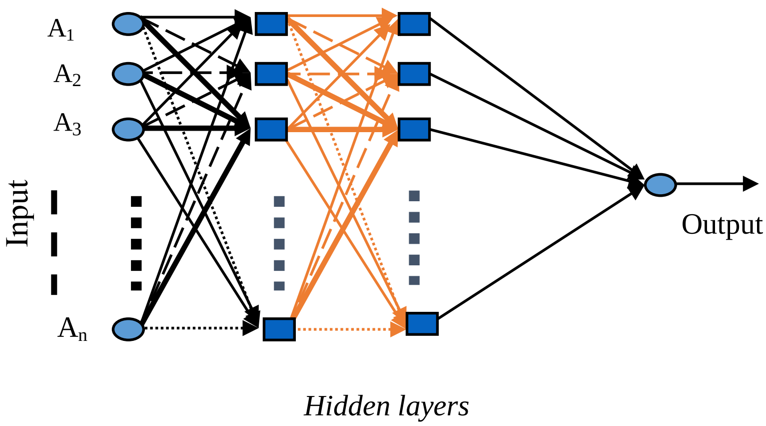

Fig.1. Multilayer Back Propagation Neural Network (BPNN) with One Output Neuron.

3.2.1. Back Propagation Algorithm

The three-layer feed-forward Back Propagation Network (BPN) is the most popular neural network structure [27] [28], which consists of an input layer, a hidden layer and an output layer. The layers are connected through the neurons of each adjacent layer. Due to the transfer process known as the activation function of the hidden layers, the network captures nonlinear phenomena. Information passes only from the forward layer, which is a designated synaptic weight, and then to the next connecting layers. Each neuron j receives input signals from neuron i in the previous layer. This is obtained by:

$$y_j^n = f\left(net_j^n\right) \tag{4}$$

Where y_j^n is the output of the n-th layer; f is the activation function, widely employed by the logistic sigmoid, hyperbolic tangent sigmoid and squared functions [27, 29], and net_j^n is the sum of the weight of the previous layer, which is calculated by:

$$net_j^n = \sum_{n-1}^{n} w_{ij}^n y_i^{n-1} + b_j^n \tag{5}$$

Where w_{ij}^n is the linkage weight from the neuron i to neuron j; y_i^{n-1} is the input data from neuron i to j; b_j^n is the bias on the neuron i, and n is the total number of input neurons.

The weight and bias will be adjusted iteratively through the Gradient Steepest Descent Method until the estimated errors converge on tolerance. The error function (E) is defined as:

$$E = \frac{1}{2}\sum_{j=1}^{n}\left(t_j - y_j\right)^2 \quad (6)$$

Where t_j is the desired output of the j-th neuron, and y_j is the output of j-th neuron in the output layer.

3.2.2. The Proposed Algorithm

In this study, a modified back propagation with adaptive slope and momentum parameter to update weights, is used. The proposed algorithm consists of two stags:-

- First stage: forward Propagation

1. The data representation in bipolar form, i.e. [-1, 1].
2. Multiply each element of input by its weight and take the summation and sent to the hidden layer units, according to Equations (7) and (8).

$$h_i = b + \sum x_i w_{ij} \quad (7)$$

$$h_k = \sigma_i . h_i \quad (8)$$

Where h_i is the hidden layer input, b is the bias value and σ_i is the adaptive slop of the input.

3. Computing the bipolar activation function in each unit of the hidden layer as in Equations (9) and (10). Then it is sent to all units of the top layer (output) layer.

$$z_k = f\left(\sigma_i . z_{in_j}\right) \quad (9)$$

$$z_{in_j} = \sigma \frac{2}{1+e^{-x}} - 1 \quad (10)$$

- Second stage: back propagation.

1. The output layer y_j receives a training input sample corresponding to each desired target sample, then the error is computed according to the following Equations (11) and (12):

$$s_k = \left|t_k - y_k\right| . dy_k \quad (11)$$

$$s_j = -\sum_k s_k . \sigma_k . w_{jk} . dz_j \quad (12)$$

Where s_k is output error, and dy_k is Gradient descent.

2. The formulae of updating the weights of the back propagation networks are expressed using momentum parameter according to the following Equations (13) and (14):

$$w_{jk}(t+1) = \alpha.s_k.z_j + \mu.\Delta w_{jk}(t) \tag{13}$$

$$\Delta w_{jk}(t) = \alpha.s_k.\sigma_k.z_j \tag{14}$$

Where μ is the momentum parameter.

3. Updating the weights of the hidden layer units using momentum parameter by the Equations (15) and (16).

$$v_{jk}(t+1) = \alpha.s_j.x_i + \mu.\Delta v_{jk}(t) \tag{15}$$

$$\Delta v_{jk}(t) = \alpha.s_j.\sigma_j.x_i \tag{16}$$

4. Updating the slope parameter for output units according to the Equation (17), and for the hidden layer units according to the Equation (18).

$$\Delta\sigma_k = \alpha.s_k.\sigma_k.y_{in} \tag{17}$$

$$\Delta\sigma_j = \alpha.s_j.z_{in} \tag{18}$$

4. Computational Results

The aim of this section is to provide experimental results of the proposed method. We start by a description of the data that were used in the experiments. After that, the results of forecasting using Box-Jenkins statistical models and ANN are presented. The reported results are then analyzed and compared. Typically, the common used forecast error measurements are applied for estimating the quality of forecasting methods. These error measurements are: Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared and Stationary R-squared.

4.1. Data Description

The data for consumer price indices data in the Republic of Yemen for the period (01/01/2005 – 01/01/2014), taken from Central Statistical Organization - Ministry of Planning and International Cooperation are used [7]. The recorded data contain the means of the prices of samples of items in various categories of consumer spending that people buy for day-to-day living. Table 1 shows some descriptive metrics for the available data. This table contains the highest and the lowest value of the data records as well as the mean and standard deviation.

Table 1. Some Descriptive Metrics Data for Consumer Prices Indices Data in the Republic of Yemen for the Period (01/01/2005 – 01/01/2014), Where N Is Training Data Count.

N	Mean	Minimum	Maximum	Std deviation
97	106.08	66.532	163.865	28.6436

Fig. 2 Shows the graph of the time series of the data in which the vertical axis refers to the consumer price (in YR) and the horizontal axis refers to the time (in months).

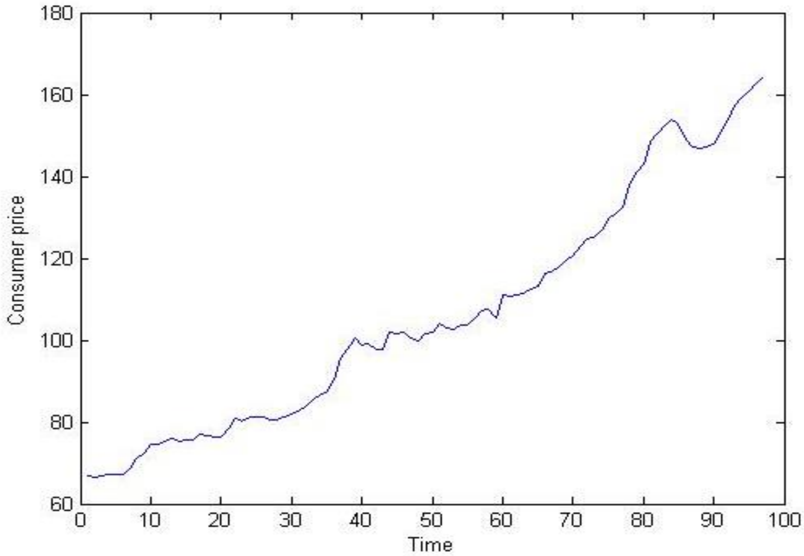

Fig.2. Graphic Representation of the Time Series.

4.2. Prediction using Box-Jenkins Statistical Models

The statistical program SPSS is used to identify the appropriate model for the data using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The identified model for this data is ARIMA (0.1.0) where it succeeded in estimated parameters significance test and it succeeded in residuals analysis test (in other words, it succeeded in the diagnostic tests for this model). Table 2 shows the forecast error measurements that illustrate the estimated values of the parameters of the model and the suitability of the time series data.

Table 2. Results for the ARIMA(0.1.0) model.

Ljung-Box Q(18)			Model Fit statistics					
Statistics	DF	Sig.	Normalized BIC	R-squared	RMSE	MAPE	MAE	Stationary R-squared
20.545	18	0.303	0.992	0.997	1.604	1.104	1.163	-1.59E-016

Fig. 3 shows the graph of the prediction on the data under study using Box- Jenkins model in which the red curve refers to the recoded data and blue curve refers to the forecasted data.

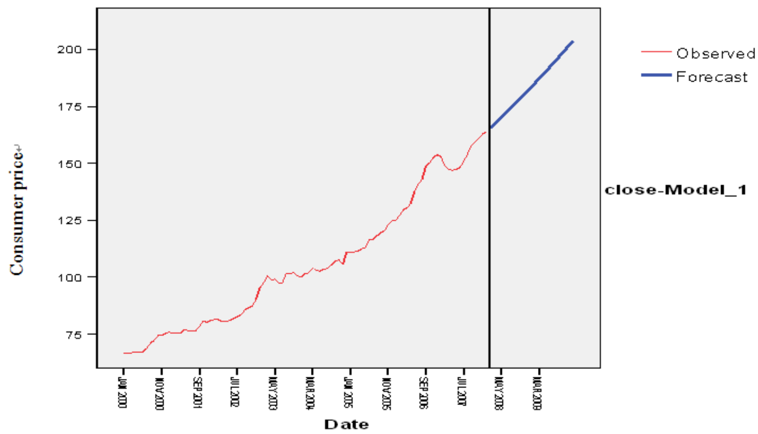

Fig.3. Prediction Results using Box- Jenkins Model.

4.3. Forecasting using the proposed ANN

The success in the implementation of the neural networks depends on the understanding and appropriate choice of the input variable. In case of achieving a forecasting regarding the time series, the network will have as a rule one output supplying the forecasted value, and the inputs may be represented through values of the variables analyzed at different previous moments.

This process of forecasting may be described like this:

$$A_{k+1} = \text{Neuralnetwork}\ (A_K,\ A_{k-1} \ldots\ A_{k-n}) \tag{19}$$

The network presents 5 neurons in the input layer and one output neuron. Fig. 4 shows an appropriate architecture of the proposed neural network, where A_{k-4}, A_{k-3}, A_{k-2}, A_{k-1}, A_k represent the inputs of the network, and A_{k+1} represents the output of the network. This architecture gives less predictive error.

For the input data, a time series will be generated as shown in Table 3. The results using this method are shown in Table 4. The predication results are shown in Fig. 5 where the red color represents the training data and the black color represents the predicted values. It is to be noted that learning rate was set to 0.1 and 17 forecasting values were used in the experiments.

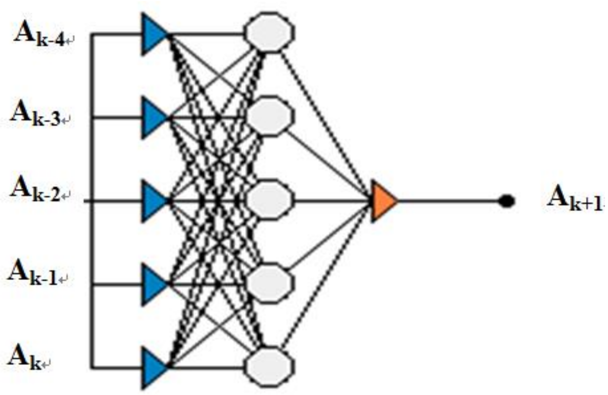

Fig.4. The Proposed ANN Architecture [5.5.1].

Table 3. Time Series Generated For Input Data.

Input Series1	Input Series2	Input Series3	Input Series4	Input Series5	Output Series
66.69	66.53	66.91	67.15	67.29	67.28
66.53	66.91	67.15	67.29	67.28	68.77
66.91	67.15	67.29	67.28	68.77	71.07
67.15	67.29	67.28	68.77	71.07	72.34
⋮	⋮	⋮	⋮	⋮	⋮
153.94	157.51	159.15	160.95	162.69	163.87
157.51	159.15	160.95	162.69	163.87	165.00
159.15	160.95	162.69	163.87	165.00	165.90
160.95	162.69	163.87	165.00	165.90	167.11
162.69	163.87	165.00	165.90	167.11	168.32
163.87	165.00	165.90	167.11	168.32	169.55

Table 4. Results for the Proposed ANN Method.

MAE	MSE	RMSE	MA PE	Network Architecture
0.3994	0.6371	0.1274	0.357	[5-5-1]

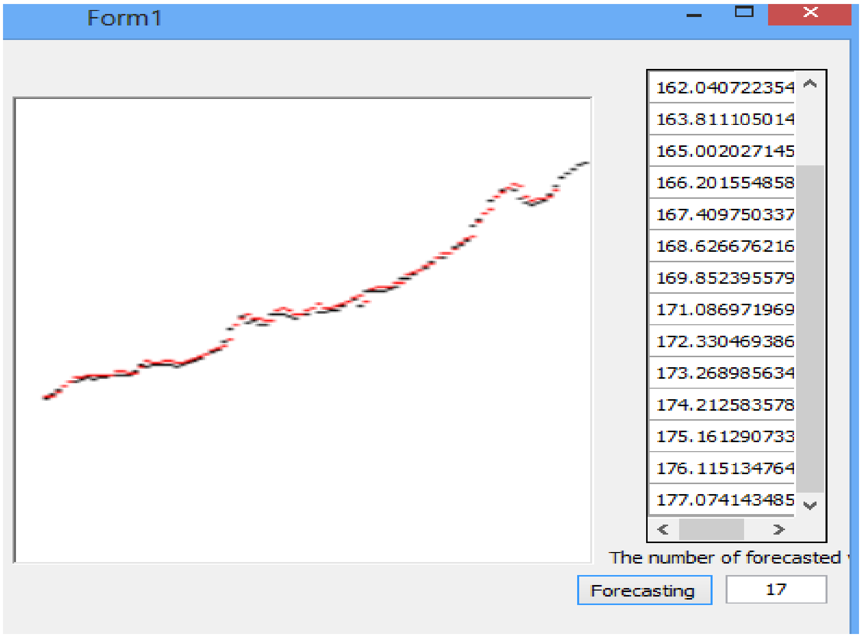

Fig.5. Prediction Results using the Proposed Neural Network.

4.4. Comparative study

Neural networks have been successfully used for time series forecasting. The classical methods used for time series predication like Box-Jenkins models assume that there is a linear relationship between input and output. Neural networks have the advantage that can approximate nonlinear functions.

Table 5 shows that, the proposed neural network[5-5-1] performs better than classical box-Jenkins model ARIMA(0.1.0) using forecast error measurements as MAE, MSE, RMSE, and MAPE, These results confirm the superiority of the proposed neural network[5-5-1] to ARIMA(0.1.0) model.

5. Conclusion and Future Work

In this paper, two forecasting methods are presented: one is based on statistical models and the other is developed using ANN. The first method employed Box-Jenkins model which is usually used to predict time series. In the second method, a modified artificial neural network model in which adaptive slope and momentum parameter are used to update the weights in back propagation neural network. The two methods are applied to predict the indices of consumer in the Republic of Yemen to the prices of the period from 01/01/2005 till 01/01/2014. For each method, the experimental results are given and analyzed based on statistical standards such as MAE, MSE, RMSE, and MAPE. The comparison between the statistical model and the proposed ANN model showed that the proposed model gave lower errors and higher accuracy for the prediction of time series data during training and testing. An important direction for function research is testing the applicability of the proposed method on large data. In this case, some improvements are required to achieve good results.

Table 5. Comparative Performance of the Two Methods.

DATA	Actual values	The proposed ANN	ARIMA(0.1.0)
01/02/2013	165.711	165.002	165.42
01/03/2013	166.580	165.9009	167
01/04/2013	167.547	167.1069	168.59
01/05/2013	168.106	168.3216	170.19
01/06/2013	169.515	169.5451	171.81
01/07/2013	170.056	170.4686	173.45
01/08/2013	171.263	171.397	175.1
01/09/2013	172.364	172.3305	176.76
01/10/2013	172.802	173.269	178.45
01/11/2013	174.036	174.2126	180.14
01/12/2013	175.932	175.1613	181.86
01/01/2014	176.050	176.1151	183.59
Sum	2049.962	2048.831	2092.36
MAE		0.344533	3.581672
MSE		0.028711	0.298473
RMSE		0.169443	0.546327
MAPE		0.202654	2.071554

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