Journal of Scientific Research and Development 2 (3): 5-10, 2015
Available online at www.jsrad.org
ISSN 1115-7569

Comparing the ability of ANN artificial neural networks and ARIMA method for predicting steel price

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Abstract: Steel industry, as a mother industry, has a special place in most countries. Close relationship between steel industry and the development indicates the fundamental importance of this product in the economy of each country. Having a reliable forecast of the price of this product becomes very valuable in the future. The main objective of this study is to assess the steel stock price prediction using artificial neural networks (ANN) method and compare it with auto-regression integration moving average (ARIMA).In this study, the stock price of steel of Mobarakeh Steel Company, as an active company in Tehran Stock Exchange, has been predicted using ANN and ARIMA prediction methods and the assumption that the artificial neural network is more efficient than the other model in predicting steel price has been investigated. Feed forward neural network with back propagation training has been used for artificial neural network. In this method, a network with five nodes in the input layer, two neurons in the hidden layer and one neuron in the output layer was selected. In the ARIMA method, according to the Box-Jenkins methodology, the model was obtained as ARIMA (1, 1,0). About the results of the prediction obtained using these two methods, the artificial neural networks model is said to perform better than ARIMA method and its forecast error is less than the second method.

Key words: Steel Price forecasting; Artificial neural networks (ANN); Auto-Regression Integration Moving Average (ARIMA); Mobarakeh Steel Company

1. Introduction

Investment and capital integration plays a very important role in the economic development of any country. The importance of this factor and its role can be clearly seen in the system of capitalist countries. Without doubt, one of the best positions to attract capital is stock. The main objective of investing in the stock market is gaining profit; thus, all investors need to predict the stock price of products in stock market. Therefore, stock price forecasting in the stock market can be seen as the most important issue that shareholders and investors have encountered.

In Iran, steel is one of the important items in the stock market that is of interest to investors. Because, steel is one the main products in the industrial structure worldwide, so that its production and consumption volume is considered as one of the certain criteria for the evaluation of success and the degree of economic development of any country. Its reason is clear and the reason is the position of steel for the production of many industrial and agricultural products from the simplest tools to the most complex of them. The history of country's steel industry shows that the industry has not been developed to meet the needs of society; rather it has been influenced by the political issues and economic ties with the outside; while today, this underlying industry of the country is founded and developed according to national aspirations and to provide for the basic needs of the country's development, which mainly relies on meeting the domestic needs as a large and comfortable market. The steel and its market is one of the most important commodities and commodity markets in the economy of Iran. Demand for steel like demand for any other production unit, is considered a derived demand; because its use in every country depends on the construction of housing units, hospitals, commercial buildings, dams, ports and so on.

This study sought to help the prediction of the price of this input for the coming years using efficient methods by identifying the nonlinear behavior of steel prices in a period of time. Determining a suitable method for the prediction of the price of this product is the aim of this study. This purpose is actualizable by forecasting future price of steel products using artificial neural networks and auto-regression integration moving average method and comparing the results of the two methods. Hence, the present study is based on these assumptions: Based on available data of the price of steel in a period of time, future price of the product can be significantly predicted using the method of artificial neural network; the method of artificial neural networks shows better performance than ARIMA method in predicting steel price.

This study is applied in terms of its objective and is carried out on the basis of descriptive and causal

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method. The population of this study is the stock price of Mobarakeh Steel Company in Iran's stock market. The statistical data of this study is the monthly steel stock price of this company during 2006-2013 that was extracted from the time series data for steel available in the statistical bases.

2. Theoretical Foundations

2.1. Artificial Neural Network (ANN)

Artificial neural networks are comprehensive and flexible and powerful tools for data analysis and modeling of nonlinear equations, with a high degree of accuracy. The most important characteristic of ANN models is their freedom of statistical assumptions about the variables, the use of parallel computing techniques and their nonlinearity. Despite the diversity of ANN models, they have a similar structure. Each neural network usually consists of three layers: an input layer that is the receiver of the resources out of system and it is compared to the five senses in the brain.

Hidden layer is of very high importance in ANN models. If there is a sufficient number of layers and units in the ANN model, it plays an important role in the learning process. This layer is merely a middle result in the process of calculating the output value; therefore, it has no counterpart in Econometrics (Nambakhsh, 2005: 56).

The output layer is like dependent variables in the regression models, and it is related to the response of the dependent variable to stimulation of the independent variables. This layer contains the predicted values of the dependent variables. In the present study, the output layer is Mobarakeh Steel stock price forecasting in different time horizons.

2.2. Auto-regression Integration Moving Average (ARIMA)

What we have understand from the econometric models up to now is that one of the goals of these studies is prediction; thus, the prediction method is to first estimate a model based on historical data and then predict endogenous variables based on the moving of exogenous variables in the future. Later, objections were proposed to this method, which was the common method in the 60s and 70s. Lucas posed a critique. He said that the structure changes and the predictions alter and foresight will be erroneous. So that other methods have been proposed for predicting variables; ARIMA model or Box-Jenkins method is one of these methods. In general, in these approaches, it is attempted to study the causal relationship between a variable with other variables in the past and accordingly predict the way of variable's motion in the future. Hence, these methods can be considered as time series analysis. Given the above discussion, it is clear that if we want to predict the future based on the history of a variable, durability or non-durability of the random process is very important, so the focus is also on the durability of variables.

3. Research Method and analysis of the results

In this paper, prediction of steel price using the two methods of artificial neural networks (ANN) and auto-regression integration moving average (ARIMA) is explained and finally, the results of the two methods are compared using accepted scientific criteria. Three sets of data were used in artificial neural network; training data was used for learning, validation data was used to examine the validity of the model and test data was used to test the model.It should be noted that the SP time series indicates monthly steel prices during the period of 2006 to 2013; this data is provided through the website of Mobarakeh Steel Complex.

4. Design stages of ANN model

In this section, the network design and selection stages will be explained and then the results of the best network in prediction are given.

First stage: This stage is the selection and training of the network. Feed- Forward neural network is used in this study. To approximate functions, feed-forward networks perform better than other networks. In this network, the output of each layer is the input of the next layer and it is one of the best learning networks with supervise and its training is forward, back-propagation. Our chosen network is a forward network with back-propagation learning that is selected from the untold or the toolbox of MATLAB software.

Second stage: The second stage is the selection of the model inputs or input layer units or in other words the model explanatory variables. In most of the time series issues with ARIMA (p, d, q),the value of p is 0, 1, or 2, and rarely takes 3 or 4. In order to make sure, input to neural network was increased from 1 to 10. The relevance of each observation was investigated up to 10 observations before that.

Third stage: In this stage, data are divided into three groups of training, crediting and testing; the major part is allocated for training and the rest to crediting and testing. In this stage we can divide data ourselves or divide them using software; in this study we have used software.

Fourth stage: The number of input variables to the first layer with the number of delays is determined. In this study, data were compiled from 2 to 10 delays and in any case, the error rate was observed and finally the data are entered to the selected network with 10 delays that has the lowest error.

Fifth stage: At this stage the number of layers of the network is selected. The selected network for this study consists of three layers, an input layer, hidden layer and output layer. More layers make network complex and only if a better output of the network is received, layers would be increased.

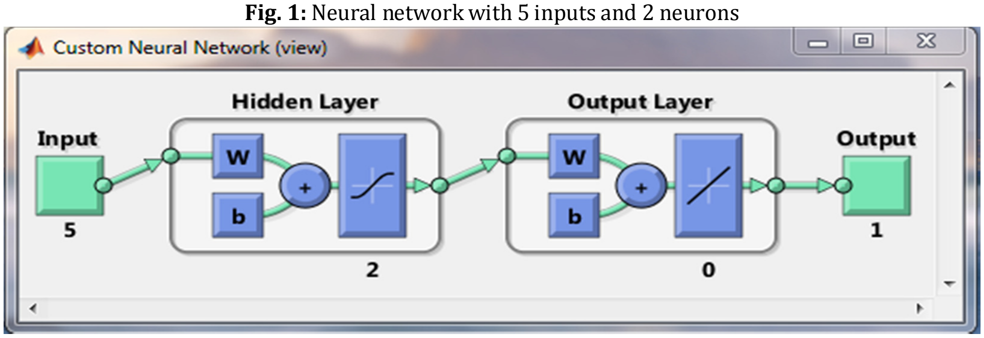
Sixth stage: The driver functions are selected for the network layer. We use tangent sigmoid function in the hidden layer and linear function in the output layer.

Seventh stage: The number of neurons in the hidden layer is determined. Although a large number of neurons in the hidden layer reduce training error, but on the other hand, the test error increases. So often we start from the low number of neurons and in the case of solutions' recovery, we increase neurons. In this study, the neurons were tested from 1 to 12 and sometimes up to 40 neurons in the hidden layer. Training error learning in the study was increased from neurons 3 and 4. Finally, 2 neurons in the hidden layer and 1 neuron in the output layer were considered.

Eighth stage: The Trainlm training algorithm is selected and the number of repetitions is set equal to 100, which is the default of software. The prediction error, the mean squared error (MSE) and the desirable error is considered 0.

According to the procedure described above, many networks were designed for the study and each were taught several times and finally the neural network was designed with 3 layers; 2 neurons were in the hidden layer, 1 neuron in the output layer, and 5 neurons in the input layer that is shown byANN52 (5 inputs and 2 neurons).

Fig. 1: Neural network with 5 inputs and 2 neurons



5. ANN52 neural network and its results

This network has 5 inputs and 2 hidden neurons and it has the lowest error from among all the networks tested; prediction and error values are brought next.

Fig.2: The rate (MSE) for the training data

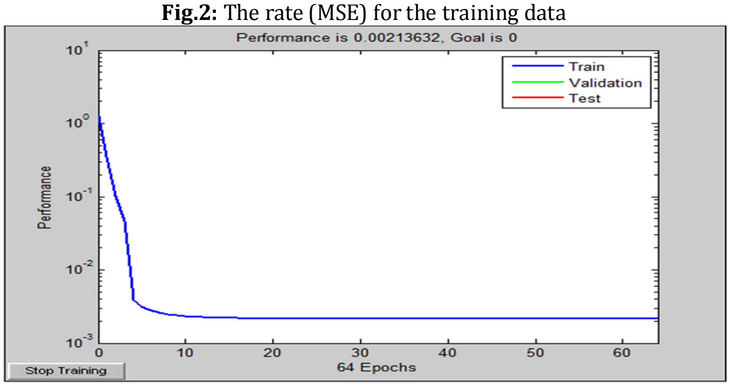


Table 1: actual and predicted values of steel price through ANN52 in 2013

Values	October	November	December	January	February	March
Actual	4070	4408	4478	4845	4418	4139
Predicted	4146.53	4430.782	4454.09	4738.87	4527.64	4207.421
Prediction error	76.53	22.782	23.91	106.13	109.64	68.421

As you can see, the predicted values are very close to the actual values. The interesting point is that the fourth predicted value has a large error that is due to the rapid increase in the real value. The network immediately has reduced its error to an acceptable level in the next value.

6. Auto-regression integration moving average (ARIMA) and its design process

In a univariate time series model, the price of steel can be considered merely a function of past values. In other words, the value of steel prices in the previous periods contained all necessary information about the determinants of the price of steel; thus, it can explain the current price of steel and predict future values. Also, if there is a need for differencing a time series d times in order to be durable and then show it in the form of the model of ARMA (p, q), it is said that the original time series is a auto-regression integration moving average model of order p, d and q that is shown as ARIMA (p, d, q). In this relationship, p is the number of auto-regression sentences, d is the number of times that the time series should be differenced in order to be durable and q is the number of moving average terms. Thus, the model of steel price prediction can generally be written as:

$$SPt = C + \alpha_1 SP^{t-1} + \cdots + \alpha_p SP^{t-p} + \beta_0 U^{t} + \beta_1 U^{t-1} + \cdots + \beta_q U^{t-q}$$

Thus, the main problem in this model is just determining the number of optimum lags of steel price and detecting the structure of the random variable in the model. Box-Jenkins method is usually used for estimating ARMA and ARIMA models; it has five steps namely making durable, diagnosis, estimation, control and prediction.

Using Box - Jenkins requires the availability of a durable series or a time series that becomes durable after differencing. For the purpose of the Box – Jenkins is the identification and determination of a statistical model that can be interpreted as a model producing real sample data from a stochastic process. There are several methods to identify durable series and nondurable series; Phillips - Peron test has been used in this study.

The identification process for ARIMA model is known as Box - Jenkins methodology that has five stages that is used for time series data in this study.

The stage of making time series durable: Table 2 shows that the steel price variable is nondurable. The durability of this time series was investigated in the first differencing and according to Table 3, it was seen that the absolute value of calculated amount is greater than the critical value in the third column and thus the series is durable.

Table 2: Philips-Prone durability test on steel price

PP Test Statistic	-2.341665	1% Critical Value*	-3.5101
		5% Critical Value	-2.8963
		10% Critical Value	-2.5851

Table 3: Philips-Prone durability test on steel price in the first-order difference

PP Test Statistic	-6.391310	1% Critical Value*	-3.5111
		5% Critical Value	-2.8967
		10% Critical Value	-2.5853

Identification stage: In this stage, the uncertain identification of model is addressed, i.e. the initial values of p, q and d are determined. Correlation diagram was used and according to the correlation diagram and autocorrelation (AC) and partial autocorrelation (PAC) diagrams, it was found that in the first stage the steel price gap enter model from the first order AR (1) and the remaining interval enter the model from the second order MA (2).

Table 4: Identifying the level of autocorrelation p and partial autocorrelation q

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.04648	14.55095	1.240227	0.2186
AR(1)	0.806972	0.077413	10.42422	0.0000
MA(1)	-0.574950	0.115599	-4.973646	0.0000
MA(2)	-0.401985	0.111551	-3.603597	0.0006

After estimating the model as shown in Table (4), according to Box – Jenkins methodology, the interval of the most nonsense coefficient is removed. Thus, MA (1) was removed and the model was re-estimated.

Table 5: Model re-estimation after removing MA (1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	26.71775	54.35890	0.491506	0.6244
AR(1)	0.321109	0.111079	2.890815	0.0050
MA(2)	-0.195266	0.116160	-1.681007	0.0967

After removal of MA (1) and re-estimation (Table 5), MA (2) was also removed and model was re-estimated.

Table 6: Re-estimation after removing MA (2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	26.29038	65.81566	0.399455	0.6906
AR(1)	0.302736	0.106917	2.831493	0.0059

After testing different combinations of models, the ARIMA (1, 1,0) model was selected.

The estimation phase: after the identification phase, it is time to estimate the model. According to the tests mentioned above, in general, the best method is auto-regression integration moving average of order p = 1 and d = 1 and q = 0 that is shown as ARIMA (1, 1, 0) and the results of the model are displayed in the Table 7.

According to Table 7, the Durbin - Watson statistics in this model is equal to 2.04. Model had no autocorrelation problem and its F-statistics also with respect to the F distribution of the table shows that all the coefficients are non-zero. According to the t-statistic, two coefficients are statistically significant.

The control stage: to ensure proper selection of the ARIMA model as the best model, after estimation the model is controlled and the correlation diagram was used for residual test. Given the correlation diagram in the annex, autocorrelation and partial autocorrelation diagrams show that the current model of ARIMA method has optimal conditions. Because by determining the appropriate lag length (1/3 views), it is observed that that each lag is in the confidence interval of the standard deviation.

Table 7: The result of predicting steel price by ARIMA model during 2006-2013

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSP(-1)	-0.697264	0.106917	2.521518	0.0000
C	18.33134	46.00695	3.398447	0.6914
R-squared	0.347100	Mean dependent var		-3.207317
Adjusted R-squared	0.338938	S.D. dependent var		511.0784
S.E. of regression	415.5358	Akaike info criterion		14.92110
Sum squared resid	13813601	Schwarz criterion		14.97980
Log likelihood	-609.7652	F-statistic		42.53019
Durbin-Watson stat	2.043275	Prob(F-statistic)		0.000001

The prediction stage: In the last step of the ARIMA model, the price of steel has been predicted using available information. In this model, like the artificial neural networks, steel price observations from October 2006 to March2013have been used for model estimation and October 2013 to March 2013 have been used for prediction. The results of auto-regression integration moving average prediction for steel price are shown in the table below.

Table 8: Prediction and actual values of steel price using ARIMA model in 2013

Values	October	November	December	January	February	March
Actual	4070	4408	4478	4845	4418	4139
Prediction	4146.53	4430.782	4454.09	4738.87	4527.64	4207.421
Prediction error	76.53	22.782	23.91	106.13	109.64	68.421

7. Comparing the results and error rate of ANN52 and ARIMA

After making predictions using both ANN and ARIMA models, in this section the two methods and their error rate are compared so that we can choose the best model. The final results of both models are shown in the following tables and figures.

Table 9: Comparing actual and predicted values of steel price using ANN and ARIMA

2013	October	November	December	January	February	March
Actual values	4070	4408	4478	4845	4418	4139
Predicted values using ANN	4146.53	4430.782	4454.09	4738.87	4527.64	4207.421
Predicted values using ARIMA	4450.079	4476.348	4502.632	4528.92	4555.21	4581.5

Table 10: values of prediction error of steel price by the ANN and ARIMA models

2013	October	November	December	January	February	March
Predicted values using ANN	76.53	22.782	23.91	106.13	109.64	68.421
Predicted values using ARIMA	380.079	68.348	24.632	316.08	137.21	442.5

8. Results analysis

We can say that if the method of artificial neural network is designed carefully and patiently enough, despite its complexity compared to conventional methods, complex functions can also be estimated. Steel price that follows a non-linear trend is also not an exception and this model can be trained for the steel price and finally make good predictions and can safely say that if this method is well designed, it has the ability to predict each economic variable.

As it can be seen in table (10), the method of artificial neural networks in addition to having the ability to predict the price of steel, they make predictions better than the conventional method of ARIMA. As noted, the selected neural network from among a large number of networks, performs better than ARIMA method and by tackling the problem of over fitting with various tricks, neural network prediction error was less than the usual method of ARIMA, which shows the high performance and power of this method in predicting and the results of the study suggest the validity of the claims.

- The results show that the ANN can predict better than ARIMA method. Therefore, research centers and units can be offered to use this method as a good and efficient one besides using econometric methods.

- Since the prices are unspecified, there is a lack of investment security and thus investment reduction. Due to the ability of artificial neural networks to predict the price of the product, using this method greatly reduces investment risk. So those who want to invest in development projects and etc. can make more accurate decisions about investing or not investing in the activities according to the predictions obtained from this method.

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