Available online at www.elixirpublishers.com (Elixir International Journal)

Economics

Elixir Economics 46C (2012) 8072-8076

ISSN: 2229-712X

Artificial neural networks ANN versus ARIMA method in predicting the TIPEX (overall index of Tehran Stock Exchange)

$Min \sum_{i=1}^{n} w_i . x_i$

$s.t \ A_{(n+w)\times n} X_{n\times 1} \geq b_{(n+w)\times 1}$

$Min \sum_{i=1}^{n} w_i . x_i$

$s.t \ y = A_{n\times n} X_{n\times 1} \geq b_{n\times 1}$

Ali Falahati and Alireza Rostami

Department of Economic, Razi University, Kermanshah, Iran.

ARTICLE INFO

Article history:

Received: 5 March 2012;
Received in revised form: 15 April 2012;
Accepted: 27 April 2012;

Keywords

Exchange,
Total index forecasts,
Artificial neural network,
ARIMA.

ABSTRACT

One of the main concerns of economists and economic policymakers is predicting future values of economic variables. One of these variables is stock index that, according to the importance of financial markets in economic development and also attractiveness of investing in this market could have many costumers. Therefore, in this study, with the daily data of years 2006 to 2012 the total index of Tehran Stock Exchange (TIPEX) using artificial neural networks (ANN), auto regressive moving average (ARIMA), and models accuracy comparison have been predicted. Results suggest that, there is no significant difference between the accuracy of neural networks models and moving auto regressive average.

Introduction

Achieving sustained and long-term economic growth requires mobilization and optimized resource allocation in the national economic level. This is not easily feasible without help of the financial markets particularly the extensive and efficient capital market. In a healthy economy, the existence of efficient financial system in the proper distribution of capital and financial resources is essential. Nowadays, stock exchange is one of the economic bases of developed or developing countries through it, the financial facilities and funds gather for economic development goals. Stock exchanges established many years ago in developed countries for (as a movable capital markets), and investigating the changes in the stock index can reveal currency, financial, economic, and even political and social fluctuations.

In other words, the Stock Exchange and consequently the indices act like thermometers which imply the health or disease of society's economy. Each time this thermometer shows swings in the economy it implies on existence of money and capital movements and booming Businesses and when it shows weakness it implies on stagnation, recession, and lack of capital formation (Bolouriyan, 1992).

Therefore, the prediction index is one of the main concerns of investors and policymakers. Naturally in this way, the methods with lowest prediction errors have appropriate survival and functional ability. In this regard, for many years, mathematical and econometrical methods are the only patterns that were strongly confirmed and used, but in many cases had drawbacks. With the creation of artificial intelligence techniques, such as neural networks, especially when an appropriate mathematical relationship between data and the dependent and independent variables cannot be formed, many hopes were created. These hopes continued until they became replaceable with the mathematical methods.

In the past, the technical analysis methods which mainly based on statistical methods and assumptions such as linearity have been used in the stock transactions processes to predict market fluctuations. But since the stock market is a non-linear system due to the political, social and psychological, and even climate factors, so the use of these traditional tools for accurate decision making in stock trading are difficult. In other words, stock markets are very complex and such complexities are inherent characteristics of such systems. Solving these complexities always has been a dream to traders and they extremely require powerful tools in their decision makings. Human's ability for data analysis was not satisfying and traditional methods also had not very promising results. Stock market's dynamic movements and its unpredictable, chaotic and non-linear behaviors somewhat outdated the traditional tools. Therefore, use of artificial neural networks to a large extent can help to overcome these problems and assist the traders. A brief look at the performance of the Tehran Stock Exchange shows that, in some periods, it has enjoyed considerable growth. Continuing upward trend, along with desire, can be worrisome. This trend is favorable as it is a symbol of Iran's capital market in finding its real place in the country's economy and is disturbing as these successes usually are not sustainable and encounter with sudden or gradual recession. In this regard, predicting the stock index with least errors possible in order to identify stock market boom and recession factors, and ways to maintain it and prevent the premature collapse of the stock market and its development has a great importance. The most important objective of this research according to above mentioned issues is investigating the function of neural networks and ARIMA model in predicting and measuring Tehran Stock Exchange general index and compare the prediction errors of two methods. The required studies, surveys, and statistics collected via library and internet-related searching in literature and research history from various valid sources. The most important source for gathering information about the index was Tehran Stock Exchange database.

Literature Review

Using neural networks in the field of economics returns to the last years of 1980s. In those years, several models for predicting exchange rates, stock prices, and indices of the

Tele:
E-mail addresses: emamemostafa@yahoo.com

various stocks have been made such as works of White (1988). Hill and colleagues (1994) examined a series of experimental and applied researches to compare the predicted results of neural networks and statistical models. They also presented better results with the data with more repeats. This issue had researches to think that the data with more repeats have higher nonlinear processes. Moshiri & Cameron (2000) compared the performance of artificial neural networks with other traditional econometrics and time series methods for predicting the inflation rate of Canada. In their work, they compared the neural network with the ARIMA, BVAR and VAR structural models for different time series, mean square of errors (RMSE), and mean absolute errors (MAE) and showed that, the neural networks are able to nicely predict Canada's inflation rate, even better than traditional econometrics and time series methods. Raposo & Cruz (2002) used neural networks to fundamental analysis of investments in the stock. This research studied using neural networks to predict the changes in stock prices of Brazilian common companies in the Sao Paulo Stock Exchange. The results showed that, neural networks are very suitable to predict long-term stock price index using fundamental analysis.

Farjam Nia et al (2007) compared the predictive ability of ARIMA models and artificial neural networks for daily price of oil in period of April 1983 to June 2005. In their work, after modeling by artificial neural networks in order to identify share participation of each input parameter in this model, the sensitivity analysis was used. Results show the superiority of artificial neural networks in predicting daily price of oil. Zara Nejad et al (2008) compared the artificial neural networks and ARIMA models for predicting daily exchange rates in period of March 2006 to February 2009. The results showed that, the artificial neural network approach offers better estimates than ARIMA method. Some of other similar works in using artificial neural network are the woks of Ghasemi (2000), Moshiri (2001), Asghari (2002), Moshiri et al (2002), Azar et al (2003) Nasery (2003) and Moshiri & Forutan (2003).

Methodology and Data

In this study, with regards to the nature of investigated variable, because its future values are largely dependent on previous values we used single-variable time series models for prediction because first, design and implementation of these models are fast and relatively simple and their prediction quality are comparable with multivariate prediction models and second, information of other relevant variables may not be available or obtaining them may have unexpected costs and be time consuming and third, with using this method we can realize how extent of index variation can be explained by its previous values.

Fundamental ARIMA model structure consists of four stages as follows: model explaining and identification, parameter estimation, detection and understanding the model, and finally predicting and being logical.

ARIMA (p, d, q) model is general, where p is model's auto regressive order , q is model's average moving order, and d is model's differential order (for model staticizing).What makes this model more completer than others, is appropriate conversion to become reliable.

In recent years, there was a continuous movement, from purely theoretical researches to applied researches, especially in the field of information processing, for which there is no solution easy solution. Considering this, a growing interest emerged in the theoretical development of free models of dynamically intelligent systems that are based on experimental data. Artificial neural networks (ANN) are in this class of dynamical systems which transfer the knowledge or the rules behind the data to network structure through processing on experimental data. Therefore these systems called intelligent systems. Because, based on calculations on numerical data or examples, they learn general rules. These models try to model human brain's Neuro – Synaptic structure. Implementation of the wonderful features of the human brain in an artificial system (man-made dynamic systems) is always tempting and desirable. There are many efforts from researcher in this field during last years, but results of these efforts regardless to the valuable finings, was increasing believe of the fact that, the human brain is unachievable. Hence, the application of these models by the researchers to detect trends and patterns in the data as well as knowledge creation from the data is pervasive.

Great flexibility of these models is another factor that led to pervasively use of it in all backgrounds of knowledge. One of the major applications of neural network models is prediction and estimation of particular variable referring to a number of inputs. This means that neural network models using a series of inputs and outputs estimate the relationship between input and output variables similar to non-linear regression models. In this model, all of the model's data divided into two training and experimental groups. Then, all experimental will be removed from the model and using the training data, the model will be estimated. After model estimation the experimental data will be used for testing. These data includes approximately 10 to 20 percent of the total data, and in some neural network models, the experimental data consists up to 25% of the total data. The main goal of the experimental data is that they can be used to compare the predicted results of experimental data with the real answer. It is obvious that, the difference between dependent variable predicted by the model and its actual amount from experimental data indicates the error in terms of average absolute error value, or sum of squares of error. With continuing the training process, the amount of errors minimal zed through certain processes related to the learning algorithm.

Determine the size of the neural network for always was a question to the researchers and lots of works have been done in this field. In 1986, Hintom & Williams suggested a statistical method for selecting the network size and number of neurons, namely auditory view, but finally an operational model not obtained. In 1993, a series of instructions were presented as a series of estimation optimizing criteria, and the same statistical instructions have been used here. In 1996, these instructions were strongly rejected by the researchers. Since then, several techniques about neural network topology presented, but none of them had the necessary comprehensiveness. Therefore, in most of used neural network models innovative methods have been used to select the number of neurons and hidden layers.

Basically MLP network with one hidden layer is enough to functions approximation, but to determine the number of hidden layer's neurons no there is not any hypothesis and precondition on real systems and the focus is only on the experimental data that adds to the complexity of working with the network. Hence, generally the size of a hidden layer obtained experimentally.

An experimental way to determine the number of hidden layer's neurons can be formulated as follows.

For example, a neural network with a reasonable size with hundreds or thousands of inputs, the selected number of hidden neurons is a relatively small proportion of the number of inputs, if the MLP network does not meet a desirable converge solution, the number of hidden layer neurons will increase, and if the network converged and had a good generalization power was, if possible, the fewer number of neurons will be tested. Finally, an agreement will be made on suitable size based on overall system performance.

Although there are several criteria for the performance of artificial neural network such as modeling time, training time and accuracy of predictions. Most important criterion for evaluating the performance of artificial neural network is the prediction accuracy criterion. Prediction accurately defined as the difference between actual and predicted values by the network. Some of the methods for measuring prediction accuracy include:

1. Turbulence rate defined as ratio of incorrect predictions on the total number of predictions.

2. Mean absolute deviation of error defined as $\mathrm{MAD} = \frac{\sum|e_i|}{N}$.

3. Mean absolute percentage error defined as $\mathrm{MAPE} = \frac{1}{N}\sum\left|\frac{e_t}{y_t}\right|$.

4. Mean square error defined as defined as defined as $\mathrm{MSE} = \frac{\sum e_t^2}{N}$.

5. Root mean square error defined as $\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$.

6. Statistic of U Tile defined as ratio of model's root mean square error on a basic model's root mean square error where, the value of predicted variable is assumed to be constant.

$$U = \frac{\sqrt{\frac{\sum e_t^2}{N}}}{\sqrt{\frac{\sum(y_{t-1}-y_t)^2}{N}}}$$

According to the above relationship, the prediction in the next period simply takes the real value from the previous period. The more size of U statistic is closer to zero, the higher is accuracy. Usually the values less than 55% are acceptable. The models in which U statistic are larger than one will reject because, in this case the predictions accuracy is worse than basic model.

In the above relationship **e** is prediction error, **y** is real value, **N** is the number of components, and the **t** is time.

The Tehran Stock Exchange Index data have been collected on a daily basis during the 2006-2010 from databases of Tehran Stock Exchange. In total, the indices gathered over 1200 working days and 75 percent of them (900 days) as training days entered in designed neural network. Then 300 outputs extracted as network prediction.

Results

In this study, ARIMA model which is a linear - random model and one of the oldest econometrics time series was used. To predict using AIRMA model we must first determine time series of stock price index with regards to durability and its order. Therefore we used Dickey - Fuller generalized test (ADF) to examine durability of stock price index time series. As can be seen in Table 1 there is no unit square in significance level of 1the order of series (d) is zero.

Table 1: Test results of generalized Dickey - Fuller test for TEPIX variable

Variable name	Test statistic in significance level			generalized Dickey - Fuller statistics
	10%	5%	1%	
TEPIX	-2.73	-3.015	-3.988	-16.332

In order to determine auto regressive (AR) order and moving average (MA) to estimate the ARIMA (p, d, q) model the AC and PAC plots have been used. Results show order of 3for AR and 1 for MA is 1. Estimation results of ARIMA (3, 0, 1) or ARMA (3, 1) model as follows

$$\begin{aligned} \mathrm{TEPIX} &= \underset{(52.168)}{9858.84255} + [\mathrm{AR}(1) = \underset{(11.752)}{0.45258124}, \mathrm{AR}(2) = \underset{(7.911)}{0.328554712}, \\ & \mathrm{AR}(3) = \underset{(10.802)}{0.442548201}, \mathrm{MA}(1) = \underset{(60.205)}{0.9366584701}, \mathrm{BACKCAST} = 6] \end{aligned} \qquad (1)$$

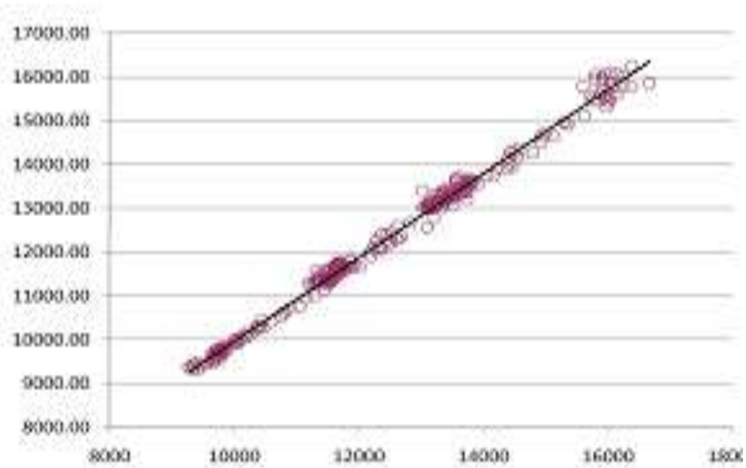
The results obtained from above model, is given in Table 2(the numbers inside parentheses are t statistic).

Table 2: Results obtained using the ARIMA

Determination coefficient(R^2)	89.3%
Intercept	411.8
Slope	0.83

Given that the TEPIX is a continuous variable, to compare real and estimated data the regression model was used. This means that, if the slope of the regression line in the diagram was close to 1and the intercept was close to the origin of coordinates, the linear regression model nicely estimate the actual values. Figure 1 shows the comparison between real data and estimation. The slope of line is 0.83 and low distance of intercept from the origin (411.8) shows a strong correlation between real and estimated data. Also, the determination coefficient of 89.3 percent confirms this. In other words, this Model can explain 89.3% of the real data. Therefore, ARIMA model have appropriate efficiency in estimating general index of stock.

Figure 1. The comparison of observed and predicted data using ARMA model



Neural networks as one of the most widely used models for estimating and predicting is very flexible and has many features. In this section, considering the ARMA (3, 1) model and to compare this model with neural networks model the neural network model designed with three inputs (AR order), one hidden layer and one neuron in output layer to estimate. With varying functions and the number of hidden layers' neurons we tried to select a network with lowest average error.

In order to estimate the neural network models for above mentioned data the post-error training method was used. Using NEURAL NETWORK software to find the best network, about 67 types of networks were tested. The most successful network to estimate TEPIX with least mean error was a three-layer neural network with three neurons in the hidden layer and tangent hyperbolic activation function in hidden layer and linear function in the output layer. Using obtained neural network model, the experimental data were analyzed and the obtained values were compared with the real values of total stock index. As can be seen in Table 3, the designed model correctly estimated 78.6% of total stock index. Therefore, neural network has a high efficiency in estimating the total stock index. To demonstrate the efficiency of neural network models in estimating the total stock index first, the real and estimated data was sorted ascending and then, using the linear regression the value of R^2 calculated. Figure 2 shows the results of this comparison.

Figure 2. The comparison of observed and predicted data using neural networks

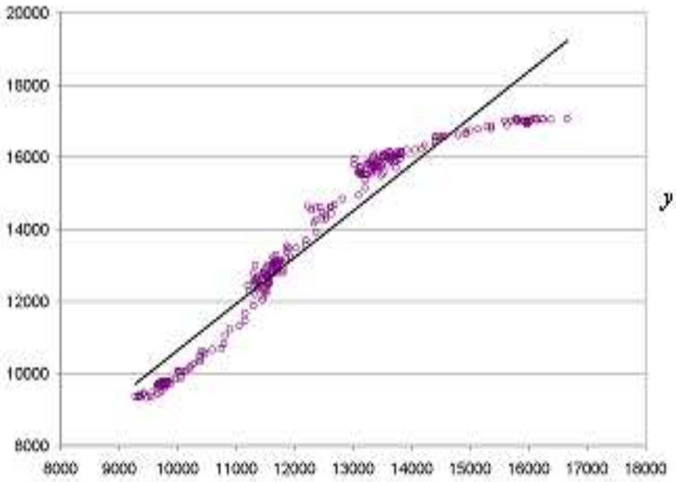


Table 3: Results obtained using artificial neural networks

Determination coefficient(R^2)	**78.6%**
Intercept	-324.4%
Slope	1.255%

As mentioned earlier the most important criteria to evaluate models performance is the prediction accuracy. Prediction accuracy defined as the difference between real values and values predicted by the model. The following table summarizes and compares the performance criteria.

Table 4: Performance comparison of results from obtained ANN and ARIMA methods

Method	**Turbulence Rate**	**MAD**	**MAPE**	**MSE**	**RMSE**	**U tile statistic**
ANN	0.8533	1218.23	8.369	0.000198	0.0125	0.000063
ARIMA	0.6266	148.70	1.035	106,523	298.582	0.152530

According to the above results, it is clear that based on rate of turbulence, MAD, and MAPE the performance of ARIMA method is better than artificial neural network and according to other criteria, especially U tile statistic that is almost zero, Artificial Neural Network has a very small error in predicting total index. With respect to other internal and external studies, MSE, RMSE, and U tile statistics mainly used to compare traditional econometric methods and artificial neural networks, and if we use these criteria we must recognize incomparably superiority of artificial neural networks over ARIMA method.

Conclusion

Predicting index is one of the main concerns of investors, markets, and policy makers. Naturally in this way, the methods with lowest prediction errors have appropriate survival and functional ability. In this regard, for many years, mathematical and econometrical methods are the only patterns that were strongly confirmed and used, but in many cases had drawbacks. In the past, the technical analysis methods which mainly based on statistical methods and assumptions such as linearity have been used in the stock transactions processes to predict market fluctuations. But since the stock market is a non-linear system due to the political, social and psychological, and even climate factors, so the use of these traditional tools for accurate decision making in stock trading are difficult. With the creation of artificial intelligence techniques, such as neural networks, especially when an appropriate mathematical relationship between data and the dependent and independent variables cannot be formed, many hopes were created. These hopes continued until they became replaceable with the mathematical methods. In this study, using ANN and ARIMA methods the total stock index predicted on a daily basis during 2006-2010. Results suggest that, the accuracy of network Neural in predicting total index is markedly greater, compared with the predictions with ARIMA model based on MSE, RMSE and U tile statistic. Moreover, according to the disturbance criteria rates, MAD, and MAPE the performance of method ARIMA is better than ANN.

The reason for this unexpected superiority ARIMA over ANN, is the nature of investigated variable namely, total index. Since a major part of the daily procedure of index is related to the day before, and its value did not encounter sudden changes during the study period, such an outcome is possible. Researchers in the future studies can use integrative methods and genetic algorithms and their comparison with conventional econometric methods to predict the index.

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