Comparative Study of Static and Dynamic Neural Network Models for Nonlinear Time Series Forecasting

Abounoori, Abbas Ali and Mohammadali, Hanieh and Gandali Alikhani, Nadiya and Naderi, Esmaeil

Islamic Azad University central Tehran Branch, Iran., University of Tehran, Faculty of Economics., Islamic Azad University, Department of Economics Science and Research Branch, khouzestan-Iran., University of Tehran, Faculty of Economics.

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Abbas Ali Abounoori

Assistant Professor, Islamic Azad University central Tehran Branch, Iran

Email*:* aba.abunoori@iauctb.ac.ir

Hanieh Mohammadali

MA in Economics, Faculty of Economics, University of Tehran, Iran,

Email: hani_1982@yahoo.com

Nadiya Gandali Alikhani

MA in Economics, Islamic Azad University, Department of Economics Science and Research Branch, khouzestan-Iran. Email: N.Alikhani@khouzestan.srbiau.ac.ir.

Esmaeil Naderi[1]

MA student in Economics, Faculty of Economics, University of Tehran, Iran,

Email: Naderi.ec@ut.ac.ir

Abstract

During the recent decades, neural network models have been focused upon by researchers due to their more real performance and on this basis different types of these models have been used in forecasting. Now, there is this question that which kind of these models has more explanatory power in forecasting the future processes of the stock. In line with this, the present paper made a comparison between static and dynamic neural network models in forecasting the return of Tehran Stock Exchange (TSE) index in order to find the best model to be used for forecasting this series (as a nonlinear financial time series). The data were collected daily from 25/3/2009 to 22/10/2011. The models examined in this study included two static models (Adaptive Neuro-Fuzzy Inference Systems or ANFIS and Multi-layer Feed-forward Neural Network or MFNN) and a dynamic model (nonlinear neural network autoregressive model or NNAR). The findings showed that based on the Mean Square Error and Root Mean Square Error criteria, ANFIS model had a much higher forecasting ability compared to other models.

JEL Classification: G14, G17, C22, C45, C60.

Key Words: Forecasting**,** Stock Market, dynamic Neural Network**,** Static Neural Network.

1. Introduction

Due to the importance of financial markets, any changes in these markets will impose a major impact on the economy (Colombage, 2009). On the other hand, different changes such as economic, social, cultural and political will affect markets leading to total confusion of the investors, mistrust of the performance of the market, existence of asymmetric information

[1] Corresponding Author (Tel: +989123750790)

and, thereby, loss of the public confidence in the markets (Zhou and Sornette, 2006). Therefore, over the past few decades, in order to create the optimized conditions for allocating financial resources and evaluating the performance of risk management, the accurate forecasting of the price changes of financial assets has attracted the attention of researchers and policy-makers (Cox and Loomis, 2006). The classical methods such as regression and structural models, despite their relative success in forecasting the variables, have not produced desired results, according to researcher, because these methods generally rely on information obtained from historical events. Mainly because the economic and financial issues in stock market lead to the formation of complex and non-linear relations, the use of flexible non-linear models, such as neural network models, in modeling and forecasting the market indexes can yield impressive results (Aladag et al., 2009). On the other hand, the use of flexible nonlinear models, such as neural network models, is a response to the lack of consensus on rejection or acceptance of the efficient markets hypothesis. Despite the complexity of these methods in the process of pricing, they have the ability to forecast the future prices with acceptable error. So far, there have been several published results on forecasting stock market prices. Melin et al. (2012), Gursen et al. (2012), Soni (2011), Dase and Pawar (2010), Jibendu (2010), Li and Liu (2009), Pritam (2008), Thenmozhi (2006) examined the stock market in different regions of the world using artificial neural network models. Also, Sahin et al. (2012), Georgescu and Dinucă (2011), Mehrara et al. (2010), Tong-Seng (2007), Ghiassi et al. (2006), Sheta and Jong (2001) forecasted the time series using multilayer feed-forward neural network (MFNN), Nonlinear Neural Network Auto-Regressive model with exogenous inputs (NNARX), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) methods. The striking point in all those studies is that, different models of neural network have a very high accuracy in forecasting the market in comparison with the classical models.

Generally, the first step in forecasting a series is its potential predictability. Therefore, checking the “efficient market hypothesis” or, in other words, the predictability of stock return using the available information is of a lot of significance. In general, "efficient market hypothesis" was proposed because of the inability to forecast the stock price due to influence of various factors (Garanjer and Timmermann, 2004).According to the efficient market hypothesis, prices in the stock market follow a random walk process. Because of the fast flow of information in the market and its impact on the stock price, stock return cannot be forecasted based on past changes in the prices (Cootner, 1964).The efficient market hypothesis in its more developed form suggests that if stock return was predictable, which is impossible in a stable economy, many of the investors would be able to earn unlimited profits (Garanjer and Timmermann, 2004). Many studies have been done on the efficiency of stock markets most of which have found evidence of inefficiency of these markets. It should be noted that, although a poor efficacy in the stock market has been verified in some studies, however, due to the random appearance of the stock indexes, a specific nonlinear process can be realized. Therefore, in such circumstances, these indicators are inefficient, and no distinction can be found, based on the linear test, between this feature and random walk model (Scheinkman and Lebaron, 1989; Hou et al, 2005; Abhyankar et al, 1995).

The present study is an attempt to, first, compare the static and dynamic neutral network models, which have been used in this study and, second, to find which of these models can make a more accurate forecast the return of Tehran Stock Exchange (TSE). For this purpose, daily time series data were used from 25/3/2009 to 22/10/2011 (616 observations) out of which 555 observations (about 90% of the observations) were used for modeling and 60 for out-of-sample forecasting. Thus, before modeling the stock market index, based on the variance ratio test and BDS, efficient market hypothesis test will be examined. If the hypothesis is rejected, the BDS test will examine the linearity or non-linearity of the variables to ensure the possibility of using neutral network models in forecasting these variables. In line with this, then a brief overview will be made of the types of neural network models used in this study and their associated properties.

2. Methodology

2.1. Neural Network Models

Despite its novelty, Artificial Intelligence (AI) has obtained the attention of scholars and researchers. Different types of artificial neural networks attempt to emulate the human mind or the learning process using computational methods, automate the process of knowledge acquisition from data and solve great and complex problems. Artificial neural networks have many applications such as data classification, function approximation, forecasting, clustering, and optimization (Ripley, 1996; Krose, 1996) .Using artificial neural networks has many considerable advantages; first, neural networks have a high similarity with the human nervous system, and unlike the traditional methods, they are data-driven self-adaptive methods, which have only few assumptions for the problems. In other words, they are model-free; second, in addition to their high-speed information processing due to parallel processing, neural networks have a very high generalizations; finally, because neural networks have more comprehensive and more flexible functional forms compared to the traditional statistical methods, they are Universal functional approximates. Neural network models are distributed parallel processes with natural essence, and their main feature is the ability to model a complex non-linear relation without any presuppositions about the essence of the relationships between the data. There are two types of neural networks: dynamic and static networks (Deng, 2013; Chiang et al. 2004; Tsoi and Back, 1995). Static networks, such as Adaptive Neuro-Fuzzy Inference Systems and Multi-layer Feed-forward Neural Network, have no feedback, and the outputs are calculated directly based on their connection with Feed-forward inputs. But in dynamic neural networks, such as nonlinear neural network autoregressive (NNAR), the outputs depend on the current and past values of inputs, outputs, and the network structure.

2.2. Static Neural Network Models

2.2.1. Feed-Forward Neural Network Models

The simplest form of a neural network has only two layers, output layer and input layer. The networks act as an input-output system. In these systems, to calculate the value of the output neurons, the value of the input neurons is checked by a transfer function or activator. Besides the input and output layers, the multi-layer neural networks use the hidden layer because it will improve the performance of the networks. First Rumelhart et al. in 1986 and since then many authors, such as Nielson (1987), Cybenko (1989), Funahashi (1989), Hornik et al. (1990), and White (1992), have demonstrated that Feed-forward neural network with one logistic activation function in the hidden layerand one linear activation function in the output neuroncan approximate any function with the desired accuracy.

2.2.2. Fuzzy Neural Network Models

The theory of the fuzzy set was introduced in 1965 by Lotfi Zadeh. Reasoning or fuzzy logic is a powerful method with wide applications for problem solving in industrial control and information processing. This method provides a simple way of drawing definite result from weak, indefinite, and vague data. The most important feature of the Fuzzy method is its ability to work with approximate data and find explicit solutions. When the pattern of uncertainty, due to the inherent variability or uncertainty, is beyond randomness, the theory of the fuzzy set is an appropriate method for the analysis of complex systems and decision processes. Unlike classical logic, which requires a deep understanding of a system, precise questions, and explicit numerical values, fuzzy logic allows us to model the complex systems (Wanous et al, 2000). In general, fuzzy logic has three distinct stages: first, Fuzzification, which converts the numerical data in the real-world to the fuzzy numbers; second, Aggregation, which calculates all the fuzzy values, all between zero and one; and third, Defuzzyfication, that includes the inverse transformation of obtained fuzzy numbers to the numerical data in the real-world (Tsipouras et al, 2008).

2.3. Dynamic Neural Network Models

These models have numerous applications in different areas such as forecasting financial markets, communication systems, power systems, classification, error detection, recognizing voices, and even in genetics. One of the most frequently used models among dynamic neural network models is the NNAR model. This model is developed by adding an AR process to a neural network model. Dynamic neural network (NNAR) has a linear and a nonlinear section; its nonlinear section is estimated by a Feed-Forward artificial neural network with hidden layers and its linear section includes an autoregressive model (AR). The general form of the NNAR neural network model is:

$$\hat{Y}(t) = f[u(t), u(t-1), u(t-2), ..., u(t-n_u), y(t-1), y(t-2), ..., y(t-n_y)] \quad (3)$$

In this formula, f represents a mapping performed by the neural network. The input for the network includes two u(t) exogenous variables (input signals) and target values (the lags of the output signals). The numbers for n_u and n_y include output signals and actual target values respectively which are determined by the neural network (Trapletti et al., 2000).

The main advantage of using this model is that it is able to make more accurate long-term forecasts under similar conditions in comparison with the ANN model (Taskaya and Caseym 2005). The training approach in these models, which is consistent with Levenberg-Marquardt (LM) Training (Levenberg, 1944 and Marquardt, 1963) and the hyperbolic tangent activation function, is built on Error-Correction Learning Rule and starts the training process using random initial weights (Matkovskyy, 2012; Giovanis, 2010; Rosenblatt, 1961). After determining the output of the model for any of the models presented in the training set, the error resulting from the difference between the model output and the expected values is calculated and after moving back into the network in the reverse direction (from output to input), the error is corrected.

3. Empirical Results

In this study, the performance of static and dynamic neural networks in forecasting Tehran Stock Exchange dividend price index and cash return was compared. The abbreviations for the used variables in this paper include: TEDPIX (Tehran Stock Exchange dividend and price index), which indicates the price index and cash return, and *dlted*, which represents the return of the TSE. On this basis, the predictability of the related index will be examined by variance ratio tests and BDS test.

3.1. Examining predictability of the return of TSE

In this section, in order to explain the reasons for using non-linear models, two tests will be analyzed; first, the non-randomness (and consequently predictability) of stock return series will be considered using the Variance Ratio Test and then its non-linearity will be examined using the BDS test.

3.1.1. Variance Ration test (VR Test)

This test (Lo and Mac Kinlay's, 1988) is used to examine whether the behavior of the components of stock return series is Martingale. In this test, when the null hypothesis is rejected, it can be concluded that the tested series will not be *i.i.d*. Overall, rejection of the null hypothesis in the VR test is indicative of the existence of linear or nonlinear effects among the residuals or the time series variable under investigation (Bley, 2011).

Table 1: The results of VR test in stock series

Test	Probability	Value
Variance ratio test	0.000	6.38

Source: Findings of Study

The results of the above test show that there is no evidence that the mentioned series (and the lag series) is Martingale; thus, the process of the data is not random. Accordingly, predictability of this series is implied in this way. The interesting point is that one cannot find out whether the data process in the stock return series is linear or non-linear as suggested by the results of this test, but can conclude that it is non-Martingale and predictable (Al-Khazali et al, 2011).

3.1.2. BDS test

This test which was introduced in 1987 by Brock, Dechert and Scheinkman (BDS) acts based on the correlation integral which tests the randomness of the process of a time series against the existence of a general correlation in it. For this purpose, the BDS method first estimates the related time series using different methods. Then it uses correlation integral to test the null hypothesis on the existence of linear relationships between the series. Indeed, rejection of the null hypothesis indicates the existence of non-linear relationships between the related time series.(Briatka, 2006).

The statistics of this test (correlation integral) measures the probability that the distance between the two points from different directions in the fuzzy space is less than ε and like the fractal dimension in the fuzzy space when there is an increase in ε, this probability also changes in accordance with it (Olmedo, 2011). Accordingly, the general form of the test is

$BDS_{m,T}(\varepsilon) = \frac{T^{\frac{1}{2}}[C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m]}{\sigma_{m,T}(\varepsilon)}$. In this equation, $\sigma_{m,T}(\varepsilon)$ is an estimation of the distribution of the asymptotic standard $C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m$. If a process is i.i.d, the BDS statistics will be asymptotic standard normal distribution. In this equation, if the BDS statistics is large enough, the null hypothesis will be rejected and the opposite hypothesis on the existence of a non-linear relationship in the process under investigation will be accepted (Moloney and Raghavendra, 2011). This test can be usefully applied for assessing the existence of a non-linear relationship in the observed time series. The results of this test have been provided in Table 2.

Table 2: The results of BDS test in the stock return series

Dimension	BDS-Statistic	standard division	Z-Statistic	Probability
2	0.03678	0.003112	11.788	0.000
3	0.05957	0.004954	12.025	0.000
4	0.07071	0.005893	11.999	0.000
5	0.07201	0.006136	11.738	0.000

Source: Findings of Study

As it can be seen in Table 2, the null hypothesis, that means non-randomness of the stock return series, is rejected. So, this indicates the existence of a nonlinear process in the stock return series (there can also be a chaotic process as well). It is worth mentioning that whenever randomness of a series is rejected in more than two dimensions in the results of BDS test, the probability of the nonlinearity of this series will be high (because the opposite hypothesis is not clear in this test). So, this test can be a corroborative evidence of nonlinearity of the stock return series. Ergo, by confirming predictability and also nonlinearity of the related time series during the research, nonlinear models, i.e., ANN, ANFIS and NNARX can be used for forecasting.

3.2. Estimating static models

3.2.1. Estimating MFNN model

Considering the large importance of network architecture, in this part before different types of feed-forward neural network models, some points related to the network architecture will be mentioned. First, in order to find the optimal number of neurons, an attempt was made to evaluate different networks with different neurons using coding in MATLAB software. Therefore, 2 to 20 neurons were evaluated in two- and three-layered networks; each one was trained 30 times and in order to compare their performance, the errors in the test data which included 30% of the whole data (randomly), were set as the criteria. Finally, the optimal number of neurons was found to be 8 and the optimal number of layers was determined to be 2. Furthermore, from among different algorithms, Traincgp had the best performance.

Another point to be mentioned after designing the network is the use of 5 lags of the dependent variable and also a dummy variable (the criterion for selecting them was the abnormal shocks to the time series under investigation in a way that the shocks greater than 3 standard deviations were regarded as the abnormal shocks) were considered as the input variables to the model. Based on this structure, the related variable was forecasted (see Table 3 for the results).

Table 4. Estimation of different MFNN models

Rows	Models	MSE	RMSE
1	MFNN *(*5lagofdlted*)*	2.63*10^-5	5.13*10^-3
2	MFNN *(*5lagofdlted&DUMMY*)*	1.94*10^-5	4.41*10-3

Source: Findings of Study

As shown in Table 3, the results of these models are indicative of a desirable performance in terms of having fewer forecasting errors considering the dummy variables.

3.2.2. Estimating ANFIS model

The modeling method used in ANFIS is similar to other system-recognizing techniques. In the first stage, a parametric system is considered as the assumption and then input and output data are collected in the form which is applicable in ANFIS. Then this model can be used for training the FIS model. Generally, this kind of modeling has a suitable performance when the data applied to ANFIS for training the membership function parameters include all the features of the FIS model.

Adaptive Neuro-Fuzzy Inference System has a similar performance to neural networks. Due to characteristics of this system, first the data must be converted to its fuzzy form or normalized and then the fuzzificated data are reread into the ANFIS toolbox and finally based on the different FIS functions (including psigmf, dsigmf, pimf, gauss2mf, gaussmf, gbellmf, trapmf and trimf), the best function will be selected.

For selecting the type of FIS function in the ANFIS model, the following procedure was followed. Due to the large volume of the data, each function was executed for 50 inputs (which have been selected randomly) and the real values and output values of the network will be obtained. Then the errors related to each function were calculated and finally the best Fuzzy Inferencing System (FIS) was selected. The results were indicative of the fact that, in the present study, two Gaussian FIS functions (gaussmf and gauss2mf) have the least number of errors and consequently the highest level of accuracy (gaussmf showed a better (though not significant) performance). After selecting the best FIS function, the optimal network estimated (trained) and obtained the output values of the system (the simulated values or out-of-sample forecasting). Therefore, based on the gaussmf fuzzy inferencing system, the number of forecasting errors of the fuzzy neural network will be estimated in out-of-sample forecasting of the stock return series in two different AFFIS models, one having five lags of the dependent variable and the other having five lags as well as the dummy variable which includes the structural breaks in the stock return series during the period under investigation (see Table 4 for the results).

Table 4. Estimation of Forecasting Criteria by Using ANFIS

Rows	Models	MSE	RMSE
1	ANFIS *(*5lagofdlted*)*	2.01*10^-5	4.48*10^-3
2	ANFIS (5lag of dlted& DUM)	1.47*10^-5	3.83*10^-3

Source: Findings of Study

As shown in Table 4, the results of the fuzzy neural network with the input data of five lags and the dummy variable, are more desirable in terms of the fewer forecasting errors compared to models with five lags of dependent variable (it should be noted that considering the fact that the validation data are not considered in the fuzzy neural networks, this value was set as zero in other models and for testing the performance of different models, the test data were only used).

3.3. Estimation of dynamic model

As mentioned, the first step in modeling nonlinear models based on neural networks is "network architecture". Therefore, before comparing different NNAR and NNARX models, the architecture of dynamic neural network should be explained.

Table.5. Network Architecture

Value	Design factor
NNAR & NNARX	Network type
10	Number of neurons in first hidden layer
1	Number of neurons in second hidden layer
Feed-Forward Network	Preprocessing function
LM [2]	Conversion function of layer

[2] Levenberg-Marquardt

Based on the network architecture that was defined in Table4, estimation and comparison of different NNARX models are offered .As in the previous models, a dummy variable has been used as the input variable.

Table 6: Estimation of Forecasting Criteria by Using NNARX

Rows	Models	MSE	RMSE
1	NNARX (1)	5.31*10^ (-5)	7.29*10^ (-3)
2	NNARX (2)	5.03*10^ (-5)	7.09*10^ (-3)
3	NNARX (3)	4.72*10^ (-5)	6.87*10^ (-3)
4	NNARX (4)	4.32*10^ (-5)	6.57*10^ (-3)
5	NNARX (5)	4.16*10^ (-5)	6.45*10^ (-3)
6	NNARX (6)	4.36*10^ (-5)	6.60*10^ (-3)
7	NNARX (7)	4.89*10^ (-5)	6.99*10^ (-3)
8	NNARX (8)	5.54*10^ (-5)	7.44*10^ (-3)
9	NNARX (9)	5.97*10^ (-5)	7.73*10^ (-3)
10	NNARX (10)	6.38*10^ (-5)	7.98*10^ (-3)
11	NNARX (15)	7.83*10^ (-5)	8.85*10^ (-3)
12	NNARX (20)	8.26*10^ (-5)	9.09*10^ (-3)
13	NNARX (30)	11.71*10^ (-5)	1.08*10^ (-2)

Source: Findings of Study

As shown in Table 5, the NNARX(5) model (using ten lags of the stock return index and the dummy variable introduced) has had the best performance in comparison with other models based on the MSE, and RMSE criteria.

3.4. Comparing the performance of models in accuracy of forecasts

In general, MSE and RMSE are the most commonly used criteria for comparing different models in accurate forecasting of the results. In many studies, the RMSE criterion used as a measure of fitting accuracy of models and includes all the features of the MSE criteria including taking into consideration the outlier data and comparing the accuracy of models as well as showing the error differences because it is the square root of MSE (Swanson et al, 2011).

Table 7: The results of comparison of the models

Rows	Models	MSE	RMSE
1	MFNN (5lagofdlted&DUMMY)	1.94*10^-5	4.41*10-3
2	ANFIS (5lag of dlted & DUM)	1.47*10^-5	3.83*10^-3
3	NNARX (5)	4.16*10^ (-5)	6.45*10^ (-3)

Source: Findings of Study

Therefore, on the basis of the mentioned criteria, we will compare the accuracy performance of the models used in this study. The results of comparison have been presented in Table 7.
As shown in Table 7, ANFIS static neural network model has fewer forecasting errors in comparison with the dynamic neural network model, i.e., NNARX(5). However, both models

have more acceptable performances than MFNN model in forecasting the return of Tehran Stock Exchange index.

4. Conclusions

Basically, one of the most important economic theories in the field of financial markets is related to the unpredictability of the changes in the price index of the stock market which is known as random walk hypothesis. Forecasting models which have been developed for the stock prices are, in fact, a challenge against this hypothesis and attempt to show that the future trend of prices can be forecasted with an acceptable number of errors despite the complications involved in the price movements. One of these models is the static and dynamic nonlinear neural network models. These models have been rather successful in forecasting the variables that have a very complicated process.

In this study, the dynamic neural network autoregressive model and also static fuzzy neural network models (ANFIS) and multi-layer feed-forward neural network model (MFNN) were used for forecasting the return of Tehran Stock Exchange index. The results presented in Table 8 show that ANFIS model has made a more accurate forecast of stock return series. After this model, NNARX and MFNN had a better performance in forecasting this variable respectively. These results were not unexpected because the results of previous studies (e.g., Mukerji et al, 2009; Dorum et al, 2010; Kamali and Binesh, 2013) had also shown the superiority of this model (ANFIS).

It should be noted that staticity of ANFIS and MFNN models and also dynamicity of NNAR and NNARX models are due to the inherent features of these models and on this basis, in this study we compared the performance of these models in forecasting TSE. In other words, the method of analysis used in this study univariable (technical) analysis. Therefore, it can be suggested that in future studies this method can be used in forecasting other economic variables (such as gold price, oil price, exchange rate, etc.) as well as in multivariable (fundamental) analysis.

Finally, the ANFIS neural network method can be introduced to policy-makers and macro-economic decision makers as an appropriate method for making more accurate forecasts and also to investors to help them make profits by assisting them in making good investment decisions via more efficient forecasts made by this model.

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