FORECASTING STOCK INDEX MOVEMENT WITH ARTIFICIAL NEURAL NETWORKS: THE CASE OF ISTANBUL STOCK EXCHANGE

Kamalbek KARYMSHAKOV [*]
Yzat ABDYKAPAROV [**]

ABSTRACT

This study aims to examine performance of artificial neural networks (ANN) in forecasting stock market index movement. The forecasting is based on two samples of Istanbul Stock Exchange (ISE) data and each consisting of 150 observations. Forecasting performance is assessed in one, five and ten day periods. Results show that ANN gives high percentage of correctly forecasted signs. This performance is particularly evident in five days period, while conventional approach mostly uses next day forecasting. These results imply that for more efficient forecasting with ANN use of different time periods is important.

Key Words: *Artificial neural network, Forecasting, Stock Market.*

YAPAY SİNİR AĞLARI YÖNTEMİ İLE MENKUL KIYMETLER BORSASI ENDEKSİNİN DEĞİŞİM YÖNÜ TAHMİNİ: İSTANBUL MENKUL KIYMETLER BORSASI ÖRNEĞİ

ÖZET

Bu çalışma yapay sinir ağları yönteminin menkul kıymetler borsa endeksinin değişim yönünü tahmin etme başarısını incelemeyi amaçlamaktadır. Tahminde Istanbul Menkul Kıymetler Borsası (İMKB) verilerinden oluşturulan ver her biri 150 gözlemden oluşan iki örneklem kullanılmıştır. Sonuçlar yapay sinir ağlarının endeks değişimlerinin yüksek yüzdesinin doğru tahmin ettiğini göstermektedir. Sözkonusu performans özellikle beş günlük periodda daha yüksek çıkmıştır. Oysa birçok çalışmada geleneksel yaklaşım olarak bir sonraki gün değeri tahmin edilmeye

[*] Dr., Kyrgyzstan-Turkey Manas University, Department of Economics, Department of Public Finance, kamalbek.karymshakov@manas.edu.kg
[**] Research Assistant, Kyrgyzstan-Turkey Manas University, Department of Economics, yzatbek@yahoo.com

çalışılmıştır. Bu çalışma sonuçlarına göre yapay sinir ağları ile daha etkin tahmin yapabilmek için farklı zaman periodlarının dikkate alınması önemli olmaktadır.

Anahtar Kelimeler*: Yapay sinir ağları, Tahmin, Menkul Kıymetler Borsası.*

1. INTRODUCTION

Forecasting stock markets has been the object of the vast research papers applying different techniques. Among them Artificial Neural Networks (ANN) is featured as being data driven and, hence, does not require assumptions concerning data. With such feature ANN is suitable technique in handling nonlinear, highly complex and dynamic data of stock markets.

Many research papers applied both to developed and emerging economies concluded that ANN outperforms other traditional linear models. Lee *et al*. (2007) comparing SARIMA and ANN model for the Korean Stock Price Index (KOSPI) investigated that the latter is better in forecasting returns of KOSPI. Chen *et al*. (2003) in their study of application neural network to forecasting the Taiwan Stock Index state that statistical performance of ANN can be reliable. Analogously, Abdelmouez *et al*. (2007) found the superiority of neural networks over linear methods - Box-Jenkins methodology and the multiple regression method, in forecasting stock sectors on American Stock Index data.

Istanbul Stock Exchange as stock market in dynamic emerging economy has become field for artificial neural network application studies too. These studies applied ANN to predict stock return, stock index direction, market volatility and failure prediction. Among them Egeli *et al*. (2003) used two artificial neural network models - multi layer perceptron and generalized feed forward, and moving averages to predict ISE market index value. According to findings neural network models show better performances than moving averages. Altay and Satman (2005) applied three alternative models: ANN, linear regression and buy and hold models to evaluate their forecasting performance. Assessment of success of these models was based on statistical and financial performance criteria.[1] Results

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[1] For statistical performance the root mean squared forecast error (RMSE), the mean absolute forecast error (MAE) and Theil's U (Theil's inequality coefficient) used. While for financial performance the percentage of correctly predicted signs and the cumulative returns of 1 YTL (new Turkish lira) portfolios managed by alternative models used.

indicate that ANN models with daily and monthly data are not better than the alternative regression models in terms of the statistical performance, while on the financial performance ANN had better performance. Avci (2007) by focusing on the forecasting performance of multilayer perceptron models for daily and sessional returns of ISE -100 index, concludes that the performance of neural network models is time depended and varies depending on time period included in analysis. Also data frequency and input selection are noted as important factors affecting the forecast performances of neural network models.

Many studies on predictability of stock markets focus on stock market return, where differences between forecasted and actual values are taken as measurement criteria. However, according to Kumar and Thenmozhi (2009) such approach may not be effective since different players in a stock market adopt different trading strategies. Depending on direction of change traders decide whether to sell or buy. Trading strategies guided by forecasts on the direction of change may be more effective than the accurate prediction of price level. Therefore, some studies use ANN to predict direction of the ISE index. Thus, Diler (2003) examines ANN models performance in prediction of the following day index direction and concluded that accuracy of forecasted direction was 60.81 %. Yildiz *et al*. (2008) applied ANN models to predict direction of the ISE 100 index on the following day, which resulted in 74.51 % accuracy. Similarly, Şenol and Özturan (2008) comparing neural network models with logistic regression state that the former statistically outperformed in prediction of stock price direction.

Following these studies this paper aims to investigate forecasting power of the ANN model in prediction direction of change of stock market using ISE data. However, being different from other studies we do not compare ANN with other forecasting methods and do not focus only on the next day index movement, rather our goal is to measure forecasting power for different time periods. We measure performance of the model within one day, five days and ten days periods. Such approach allows test above mentioned argument on time dependency of the ANN performance.

The remained of the paper is organized as follows. Second section focuses on brief explanation of artificial neural networks. Third section describes data selection and processing. Method of model estimation is presented in fourth section. Fifth section discusses research findings and last section concludes.

2. ARTIFICIAL NEURAL NETWORKS [2]

ANN are modeling techniques that mimic the human brain and nervous system and human brain's ability to classify patterns or to make predictions or decisions based on past experience. Human brains are composed of neurons which are interconnected with each other. Each neuron takes impulses from other neurons, processes them and transmits as output to other neurons.
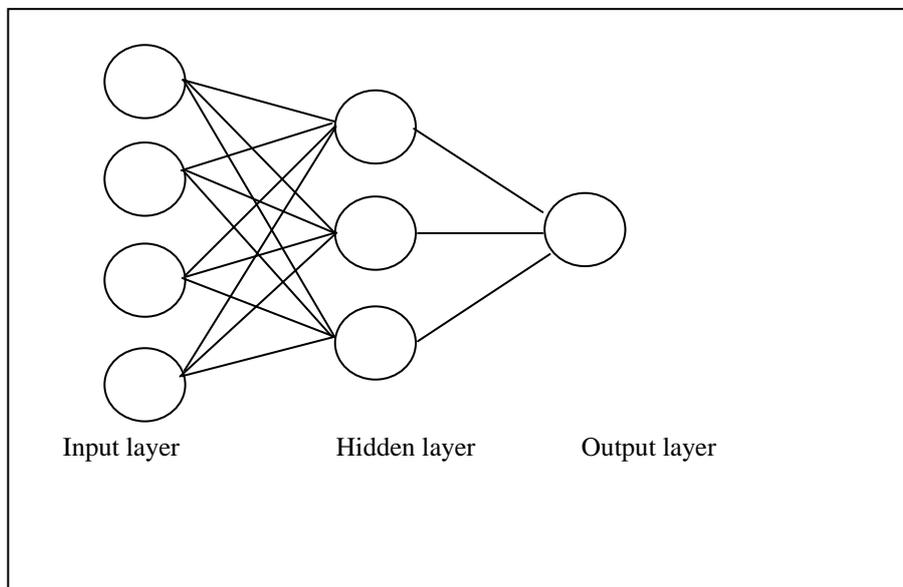

Figure 1: Artificial neuron model

These neural structures operate electrochemically. Neurons are grouped in networks, so human brain can be viewed as a collection of neural networks. ANN is composed of a collection of neurons grouped in three or more layers. Within simple three layer artificial neural networks the first layer of neurons is input layer and has one neuron for each input to the network (see Figure 1).

Each input neurons are connected to every neuron in hidden layer. If network consists of more than one hidden layer then each neuron in first

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[2] This section is based on Gately (1996) and Medsker *et al.*(1996)

hidden layer will be connected to every neuron in second hidden layer and so on. Last hidden layer will produce one output, i.e each neuron in hidden layer is connected to single output layer. Sometimes this output layer may include two or more neurons. Connections between neurons are called weights. Depending on strengths of connections weight value can range.

In Figure 1 input layer consists of four neurons, if we denote them as X_i, connections between input layer as W_{ij}, weighted sum of Xi and W_{ij} as Yi, then processing of inputs can be written mathematically as:

$$Y_i = \sum_{j}^{n} X_i W_{ij}$$

Summation function of Y_i also called as activation function. The relationships of activation function with neuron in output layer, which can be linear or non-linear, are expressed by transformation function as follows:

$$Y_{ST} = \frac{1}{1 + e^{-Y}}$$

This is a sigmoid function, where Y_{ST} is the transformed value of Y. Indeed, there are several transformation functions and choice among them depends on purpose of using neural networks.

The fundamental feature of ANN is its learning process. It learns from training and experience like human brain, in other words learns from its mistakes. During the learning process neural networks learn by adjusting the weights, which in the beginning of learning process are set randomly. The differences between actual and desired output are minimized by changing the weights. Different learning algorithms are used for error computations. In most of the studies backpropagation algorithm is considered as most effective. Moreover, this algorithm has lower memory requirements and reaches acceptable error level quite quickly.

3. DATA AND VARIABLES

Following many other studies we use following fundamental and technical variables to forecast ISE index movement:
- Daily high and low values of ISE 100 (High XU100 and Low XU100)
- Daily ISE 100 close value
- Stochastic oscillator (SCH)
- 5-day moving average

- 1,2,3-period lag values of daily ISE 100
- Gold Price and USD exchange rate

Selected time period for analysis is 01/02/2002-10/04/2007. 80 per cent and 20 per cent of data between 01/02/2002 and 02/02/06 were set to train and to test network correspondingly. Training data set is used for neural network training in order to adjust for network weights, while the latter is used to determine effectiveness of training and to test the occurrence of errors during the future network application.

Time period between 03/02/2006 and 10/04/07 are used for testing performance of the model. This forecasting period is separated into two sets in order to evaluate performance of the neural network model independently in two different samples. Therefore, expectation from the perfect performance of the model application is that there will not be differences in results of application to these two samples. The data collection is based on the Istanbul Stock Exchange and Central Bank of Turkey information.

Since used data are time series, seasonal adjustments are made to eliminate trends and seasonal variations. Outliers prevent correct neural networks training and significantly degrade neural network performance. Removing or substituting outliers in data helps neural networks to recognize patterns in data. Outliers' coefficient is selected as 3.5. Outliers above this coefficient were removed.

We should once again note that the neural networks are data-driven approach. They learn the relationship inherent among variables without requiring a pre-specification during the modeling process. Although some studies on ANN support the view that using more information, or in other words adding more inputs to neural network model improves its performance, use of extra variables may cause over fitting and weaken outcomes. So paring down the number of inputs may lead to more accurate and robust prediction. Selecting proper input variables requires trial and error. There exist several input selection methods identifying input variables which significantly contribute to performance of neural network[3]. Method

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[3] Other methods are exhaustive search and ordered search. Exhaustive search method tests all possible combinations of inputs to find optimal set. But this method is very slow and time consuming. Ordered search involves forward stepwise and backwards stepwise methods. In forward stepwise one input is added at each step until included inputs improve the performance. Having started with all inputs, backwards stepwise method removes one input at each step deteriorating the performance of neural networks.

used in this paper is the genetic search procedure. This method uses genetic algorithms which can handle difficult optimization problems. It starts with random input configurations and at each step some inputs are ignored until best input configurations are selected.

After preparation of all needed procedures to adjust and include data into analysis, data preprocessing is needed to modify data before it is fed to neural network. Preprocessing transforms the data to make it suitable for neural network. Our input data were scaled to be in range between [-1..1] following the formula:

$$PV = [L + (AC - minC)] \cdot \frac{U - L}{maxC - minC}$$

Where:

PV- preprocessed value

L-low scaling range limit

U-upper scaling range limit

AC-actual value of column vector

minC- minimum value of column vector

maxC- maximum value of column vector

For our target column vector, which is the forecasting ISE 100 index, logistic activation function is used. This activation function vary within a range [0;1]. This is particularly useful in the hidden layers of networks applied to financial historical series.

4. METHOD

Optimal contribution weights of selected variables to the network model determined within the ANN estimations are given in Figure 2 Daily high and low values of ISE 100 are given with comparatively higher weights, while stochastic oscillator, two day period lag values of daily ISE 100 and gold price have less weights among variables.
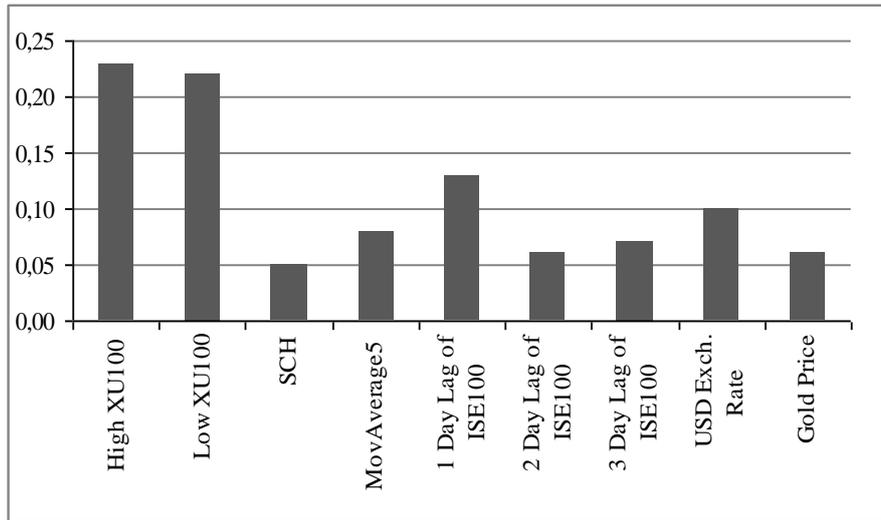
Figure 2: Input contribution factors

Units of neural networks used in this study are shown in Table 1. Batch back propagation was chosen as training algorithm. This algorithm is an advanced variant of Back Propagation where network weights update takes place once per iteration. Logistic function which has a sigmoid curve is used to produce output. Learning rate is a control parameter which affects variation of weights.

Most important feature of neural network is its ability to learn. The main idea is to construct such learning algorithm or weight update rule that minimize the error term between the output of the neural network and the actual desired output value.

Table 1: Construction of ANN model

Number of Input Variables	9
Number of Hidden Layers	1
Number of Neurons	15
Activation Function	Logistic function
Training Algorithm	Batch back propagation
Number of Iterations	10000
Learning Rate	0.05

This learning rule can be derived using gradient descent rule, the objective of which is to minimize a cost function which is:

$$E = \frac{1}{2}\sum (Y_i - W_i X_i)^2$$

Where Y_i is actual output and this cost function solely depends on neural network weights. So, the weights are adjusted at each repeated step until error reaches a minimum level:

$$W^{new} = W^{old} - \eta \frac{\partial E}{\partial W}$$

Where η refers to the learning parameter. In each iteration weights are changed according to the learning rate.

5. RESULTS

Results of the model estimation are compared with actual stock market index changes on two different samples: range of first is 03.02.2006 - 04.09.2006, and of second is 05.09.2006 – 10.04.2007. Both samples include 150 observations. Within these two samples forecasting is made in terms of three time periods: one day, five days, and ten days. Percentage of correctly forecasted signs for each period is presented in Table 2.

Table 2: Percentage of correctly forecasted changes

	1 day	5 days	10 days
First sample	70 %	82,7 %	76 %
Second sample	76.7	82 %	74.7 %

Results do not demonstrate large differences in two samples. Although as an exception may be considered one day case. Interestingly, the highest percentage for correctly forecasted signs belongs to five day period for both samples. Indeed, over all percentage of the correctly forecasted signs are quite high, above 70 per cent. Although in this study ANN model is not compared with other forecasting methods, such results once again supports arguments on the sufficiently high forecasting performance of ANN. According to these findings performance of the ANN appears to be time-dependent. With this feature the best performance may be not only from the forecasting next day, but different forecasting periods should be tested too.

6. CONCLUSIONS

Forecasting stock market index movement may be for effective than forecasting stock market return, where differences between forecasted and

actual values are taken as measurement criteria. In this study we aim to forecast movement of Istanbul Stock Exchange Index applying artificial neural networks. Although previous studies indicates high performance of ANN in comparison to other techniques in forecasting stock market index movement, this study attempted to evaluate performance in terms of one, five and ten days period using batch backpropagation algorithm

Generally results are in line with previous studies and confirm high performance of ANN. Nevertheless, forecasting of five days period resulted in the best performance. This implies that, while conventional approach on forecasting the next day index movement provided conclusions about considerable advantage of ANN in forecasting general, its forecasting power for particular forecasting period deserves attention. Although the scope of this study does not provide with absolute confidence on this conclusion, this argument may be the object of further researches on other stock markets and different time periods.

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