Forecasting the Direction of BIST 100 Returns with Artificial Neural Network Models

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***Abstract* - In this paper, Artificial Neural Networks (ANN) models are used to forecast the direction of Borsa Istanbul 100 (BIST100) index returns. Weekly time-lagged values of exchange rate returns, gold price returns and interest rate returns are used as inputs to ANN models in the training process. Results of the study showed that BIST100 index returns follow a specific pattern in time. Estimated ANN models provide valuable information to the investors and that BIST100 stock market is not fully informational efficient.**

*K**eywords** Stock Return, Forecasting, BIST100 index, Artificial Neural Networks, Back Propagation*

1. Introduction

Forecasting the direction of stock return has been regarded as highly complicated and difficult process since stock market is dynamic and chaotic in nature (Kara et al., 2011). Predicting the market price movements and forecasting the projections about future are the challenging applications. Many micro and macro economic factors interact with the stock market prices. Forecasting empowers the inventors to the existing historical data to predict and evaluate investment instruments and their directions/movements (Hadavandi et al., 2010). This is essential for the investors to make best choice among the investment instruments.

The main objective of stock market prediction is to achieve best results using minimum required input data and the least complex stock market model (Hadavandi et al., 2010). An increasing interest of professional investors in the firm's common stock will cause positive adjustments in the market price of the firm's common stock (Jones and Litzenberger, 1970). Umstead's study in 1977, one of the oldest studies, had undertaken an extensive statistical investigation of aggregate quarterly stock prices (the Standard and Poor's Index of Five Hundred Common Stocks) and their relationship to a leading indicator of business activity. The Box-Jenkins methodology is utilized to build a transfer function model relating changes in the National Bureau of Economic Research Leading Composite Index to subsequent stock price changes. The model is tested in a fifty quarter holdout sample and found to be successful at forecasting stock price changes one quarter ahead. The study (Akcan and Kartal, 2011), containing stock prices of seven companies which form Insurance Sector Index tried to be estimated with ANN models. Their results showed that all the predictions were generally good, but especially up to one month are quite successful in forecasting.

Over the years, many researchers have been focused on the methods to improve the accuracy of predictions of index value and returns of stock prices in developed and developing countries. According to an extensive literature investigation, it is appeared that many methods and algorithms are examined to promise more accurate prediction in stock market indices. Some of them are regression model, support vector machine algorithm (Liu and Hu, 2013; Xiong et al., 2014; Kazem et al., 2013), neural network (Salehi et al, 2011), data mining (Nemeş and Butio, 2013), fuzzy clustering method (Li et al., 2013) and hybrid methods (Hsu, 2013). Since the stock price time series data is characterized by nonlinearity, discontinuity and highly frequency polynomial components, predicting the stock price or its movements can be categorized as np-hard (non-deterministic polynomial) problem. These types of problems, including parameterized complexity, are more complex and impossible to solve by classical models. Therefore genetic algorithms, ANN, fuzzy logic and vector machine algorithms are examined

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for predicting the stock price or its movements. These methods may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information.

Many studies used different variables such as exchange rates, daily US dollar returns and oil prices in forecasting returns of investment instrument by ANN model (Zhang and Berardi, 2001; Kılıç, 2013; Farahani and Mehralian, 2013). Results of these studies imply that the degree of predictability of ANN can be considered as potentially useful for investors.

In some studies, results of the several methods such as regression and time series models had been compared with the neural network by using the same data. While comparing ANN with regression, AR, ARMA, SARIMA and GARCH models, neural network proved to be a better predictor but SARIMA performed better than ANN for mid-term and long term forecasting. It was opposite in short term forecasting and the Bayesian Chiao's model is much better than ANN (Carvalhal and Ribeiro, 2007; Kyung et al., 2008).

Some other studies are aimed to forecast the stock price returns and direction of their movements. ANN has become one of the most popular forecasting models in capital market studies over the last few years. In the studies, various types of ANN models were used to predict stock market prices (Nemeş and Butio, 2013; Cao et al., 2011; Kara et al., 2011; Hadavandi et al., 2010), stock price index (Kyung et al., 2008; Hosseini et al., 2011), their returns (Reboredo et al., 2012; Ferreira and Santa-Clara, 2011) and trends/the future movements (Cao et al., 2011; Kara et al., 2011; Merh, 2013).

Past studies were generally attempt to predict the returns by using past historical value of one kind of investment instruments. However, stock market prices or returns are generally influenced with the other investment instruments as previously mentioned. In the recent years, researchers have investigated the effects or relationships of various variables on stock returns and stock market indices. For instance, influence of currency rates on stock market (Morelli, 2002; Brown and Otsuki, 1993) and impact of multi variables (inflation rates, oil prices, gold prices, growth rates) on stock market indices (Dastgir and Enghiad, 2012); and relationships between oil price and stock returns (Jones and Kaul, 1996), inflation rates and stock returns (Mc Queen and Roley, 1993) are some of these studies.

The main objective of this article is to predict the direction of BIST100 index returns by using the lagged value of exchange rate returns, gold price returns and interest rate returns as input to ANN models. In recent years, several studies have used many techniques and variables to predict the future movements of stock market index, their directions and returns. But there are limited studies that use other investment instruments as inputs in the back propagation learning stage in the ANN algorithm. In this study, we have used a feed-forward back propagation artificial neural network (BPANN), a powerful system, capable of modeling complex relationship between variables, based on supervised procedure. With this respect, this study contributes to the literature of forecasting of stock market return.

The rest of this article is organized as follows. Section 2 refers to the description of ANN method, section 3 includes the sample selection, methodology and empirical results and finally section 4 concludes the article and discusses some future research perspectives.

2. Artificial Neural Network

ANN has been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by Mc Culloch and Pitts (1943).

The inspiration of ANNs comes from the desire to produce artificial systems capable of performing sophisticated a computation similar to a human's brain performs. Thereby ANN resembles the brain and provides the solution based on the representative set of historical relationship (Papale, 2003). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm (Abraham, 2005).

ANN is a popular artificial intelligence model used to acquire knowledge from datasets in different domains by applying learning techniques which work as estimators between the available inputs and the desired outputs (Gannous and Elhaddad, 2011). The units, often organized in layers, are connected by communication channels (connections) and operate only on their local data and on the input they receive via the connections.

The ANN consists of different layers. The input layer takes the input data then distributes it to the connections which connect the hidden layer and the input layer. The neurons in the hidden layers process the summation of the information received from the connections of the input layer. Then it processes the summations with its activation function and distributes the result to the next layer. This process continues down through the layers to the output layer. The neurons of the output layer process the summation of the information received from the connections of the hidden layer. Then each neuron processes the summation with its activation function. The output of the activation function is the output of the ANN (Desrosiers, 2013).

The learning phase of the ANN can be supervised or unsupervised. Supervised learning consists of giving inputs to the ANN and adjusting the weight to minimize the sum of the differences between the predicted output given by the ANN and the desired output (Desrosiers, 2013).

The accumulated operating data used in ANN training may contain corrupt and noisy data records. Therefore, to enhance the reliability of the trained ANN, a data preprocessing technique is necessary for preparing the training and testing data set (Gannous and Elhaddad, 2011, p.124). Furthermore, suitable data processing technique increases the performance of learning stage and performance of ANN.

3. Sample and Methodology

3 1 The Sample and Variable Selection

In this study, up to forth (4 week) lagged value of weekly returns of interest rates, dollar exchange rates and gold price are used as input variables in ANN models in order to predict weekly directional movements of BIST100 index value. The input and output variables are shown in Table 1. The output of the ANN models is defined by the following function;

$$BIST\_Dir = \begin{cases} 1, & if\ return > 0 \\ 0, & if\ return \leq 0 \end{cases}$$

Weekly returns of dollar exchange rate and gold price are calculated by the following equation;

$$R_{k,t} = \frac{(P_{k,t} - P_{k,t-1})}{P_{k,t-1}} \quad (1)$$

Here, $R_{k,t}$ and $P_{k,t}$ represent weekly return of relevant kth (k=1,2,3,4) investment instruments and weekly closing price of the kth instrument respectively, and t denotes the time lag.

The sample data covers 606 weekly returns between the period of January 01, 2002-October 11, 2013 which were obtained from the electronic data delivery system of the Central Bank of Turkey.

Table 1. Sample Data

Input	Variable	Description
	IRate	Weekly weighted average interest rates, applied to Turkish lira deposits
	DRate	Weekly percentage changes in U.S. dollar exchange rate according to the closing price
	GRate	Weekly percentage change in gold price according to the closing price
	BISTRate	Weekly percentage change of BIST100 index according to the closing value
Output	BIST_Dir	Weekly directional movement of BIST100 index value

3 2 Training of the ANN models

After performing so many experiments, we trained three ANN models; Model(0), Model(1) and Model(0,1), Inputs of the all there ANN models are first, second, third and forth lagged value of investment instruments (IRate, DRate, GRate). First lagged value of BISRate input changes according to the model. Model (0) covers only negative returns; Model(1) covers only positive returns and Model(0,1) covers both positive and negative returns respectively. Output of the all there ANN models are in boolean type (BIST_Dir= 0, BIST_Dir= 1). Here, 0 and 1 represents negative and positive direction.

The ANN models trained as follows;

Let $R_{k,i}$ (i=1,…,16.) denotes first, second, third and forth lagged values of investment instruments (IRate, DRate, GRate and BISTRate) which are used as input in the input layer; i, j and k represent input, hidden and output layers; n, m and p indicate number of nodes in input, hidden and output layers respectively. Each hidden node j produce an output by using following logit (sigmoid) activation function $f\ (x_j)$ which uses the weighted sum of the inputs R_i from the input layer;

$$f(x_j)=1/(1+e^{-z_j}),\ z_j=\sum_{i=1}^{n} w_{ij}R_i,\ j=1,\ldots,m. \qquad (2)$$

Here, w_{ij} is connection weights from input node i to hidden node j. The outputs from the hidden layer nodes are the inputs of the output layer nodes. Also, each output node k produce an output by using following sigmoid activation function $f\ (x_k)$ which uses the weighted sum of the inputs $f\ (x_j)$ from the nodes of hidden layer;

$$y'=f(x_k)=1/(1+e^{-z_k}),\ z_k=\sum_{j=1}^{m} w_{jk} f(x_j),\ k=1,\ldots,p. \qquad (3)$$

Here, y' denotes predicted value of the ANN model ($0\leq y'\leq 1$), w_{jk} is connection weights from hidden node j to output node k. Hence, the prediction error ($\varepsilon_t = y_t - y'_t$) is the difference between the actual status (y_t) which is either 0 (for negative return) or 1 (for positive return), and predicted direction of BIST100 return value (y'_t) in week t.

Hence, the total prediction error function of ANN given the training sample size of N is;

$$S(w)=\sum_{t=1}^{N} \varepsilon_t^2 \qquad (4)$$

Values of the all weights $(w_{ij},\ w_{jk})$ in the ANN model were determined by the following estimation algorithm:

All weights were assigned with random values initially and modified by the gradient descent algorithm according to the gradient vector of the total prediction error function;

$$w_{new}=w_{old}+\alpha\nabla E(w)\Big|_{w_{old}},\ \nabla E(w)=(\partial S(w)/\partial w) \qquad (5)$$

α is the learning parameter ($0\leq\alpha\leq 1$), and taken as α=0.0001 in this study. Iterations eventually terminated at a local minimum of the total prediction error function when $w_{new} \cong w_{old}$.

Table 2. Parameter Estimation of Model (1)

Predictor		Predicted		
		H(1:1)	H(1:2)	H(1:3)
Input Layer	(Bias)	-0,213	-0,382	-0,230
	IRate1	-0,469		0,219
	IRate2	0,046	-0,343	0,238
	IRate3	0,422	-0,151	0,000
	IRate4	0,258	0,050	0,156
	GRate1	-0,303	0,440	-0,220
	GRate2	-0,159	0,533	-0,158
	GRate3	0,103	-0,268	-0,052
	GRate4	-0,061	0,100	0,327
	$DRate_1$	0,366	0,369	0,165
	$DRate_2$	-0,092	-0,330	0,161
	$DRate_3$	0,228	-0,285	0,020
	$DRate_4$	0,249	-0,404	-0,418
	$BISTRet_1$	-0,270	0,017	0,487
	$BISTRet_2$	-0,032	-0,114	0,318
	$BISTRet_3$	0,175	-0,489	0,092
	$BISTRet_4$	0,125	0,068	-0,021
Hidden Layer 1			BIST_Dir=0	BIST_Dir=1
	(Bias)		-0,585	-0,148
	H(1:1)		0,028	-0,419
	H(1:2)		0,241	-0,304
	H(1:3)		-0,083	-0,056

After the training process we obtained the adjusted connection weights for Model (1) in Table 2. The connection weights of Model (0) and Model (0,1) are not presented here.

Here, for example connection weights between input node $IRate_2$ (second lag value of interest rate and hidden layer node H(1:1), H(1:2) and H(1;3) are 0.046, -0.343 and 0.238 respectively. Weights between hidden layer node H(1:1) and output node BIST_Dir=0 and BIST_Dir=1 are -0.585 and -0.148 respectively. The other connection weights in Table 2 can be interpreted in similar way.

Table 3 gives observed and predicted classification results of weekly direction of BIST100 returns by the estimated three ANNs model. Classification results are given for the training and testing sample. In the study the whole sample data were randomly divided two equal groups as training and testing sample; training sample was used to train (estimate) the models, testing sample was used to evaluate the models in terms of the classification achievements.

Table 3. Classification Achievement of Estimated ANN models

Observed		Predicted BIST_Dir 0	1	Correct classif.
Model (0)				
Training	BIST_Dir= 0	93	7	93.00%
	BIST_Dir= 1	84	8	8.70%
	Overall Percent	92.20%	7.80%	52.6%
Testing	BIST_Dir= 0	41	1	97.60%
	BIST_Dir= 1	23	5	17.90%
	Overall Percent	91.40%	8.60%	65.70%
Model (1)				
Training	BIST_Dir= 0	4	87	4.40%
	BIST_Dir= 1	3	151	98.10%
	Overall Percent	2.90%	97.10%	63.30%
Testing	BIST_Dir= 0	3	27	10.00%
	BIST_Dir= 1	2	58	96.70%
	Overall Percent	5.60%	94.40%	67.80%
Model(0,1)				
Training	BIST_Dir= 0	107	106	50.20%
	BIST_Dir= 1	72	190	72.50%
	Overall Percent	37.70%	62.30%	62.50%
Testing	BIST_Dir= 0	22	28	44,00%
	BIST_Dir= 1	13	59	81.90%
	Overall Percent	28.70%	71.30%	66.40%

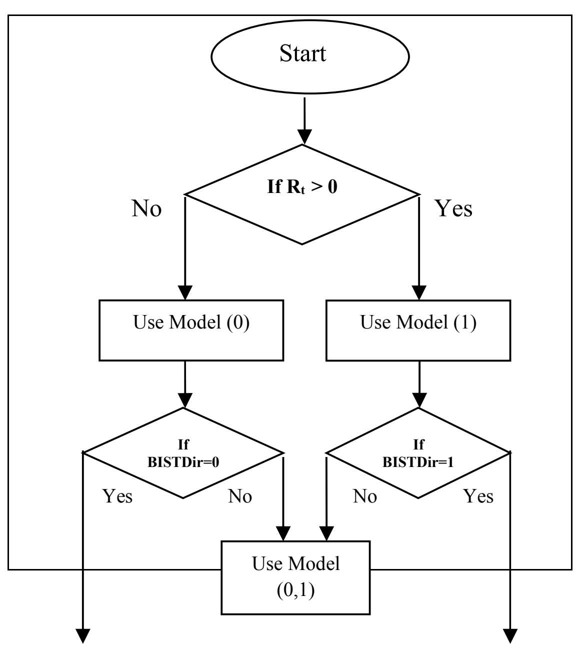
Dependent Variable: BIST_Dir

In last column of Table 3 for the testing sample we can see that if the present week return of BIST100 is non-positive, the Model (0) predicts next week as non positive direction 97.6% correctly for testing sample. If the present return is positive, the Model (1) predicts next week positive direction 96.7% correctly. However, the Model (1) does not predict negative direction (10%) accurately. At this situation, there is no matter whether the present return is either positive or non-positive, the Model (0,1) correctly predicts next week non-positive return 44% and positive return 81%. In order to eliminate these unreliable predictions and to make more accurate prediction, the three models can be integrated together for the prediction process.

Flowchart of integrated use of these models in prediction process is given in Figure 1. If the present return is positive the Model (1) should be used. If the Model (1) predicts positive return, prediction is 96.7% correct, stop the prediction. If the Model (1) predicts non-positive return do not use model (1); use model (0,1). If Model (0,1) predicts positive direction its prediction is 81.9% correct, stop prediction. If Model (0,1) predicts non-positive direction it is 44% correct, stop prediction.

If the present return is non-positive the Model (0) should be used. If the Model (0) predicts non-positive return, prediction is 97.6% correct, stop the prediction. If the Model (0) predicts positive return, use Model (0,1). If Model (0,1) predicts positive direction, prediction is 81.9% correct and stop prediction. If Model (0,1) predicts negative direction, prediction is 44% correct and stop prediction.

This result indicates that BIST 100 stock market is not fully informational efficient. In another words, Efficient Market Hypothesis (EMH) does not hold for the BIST stock market. The first level of EMH is the "weak" form which asserts that all past market prices and information are fully reflected in securities prices. Hence, technical analysis is of no use. The second level is the "semi-strong" form asserts that all publicly available information is fully reflected in securities prices. So, fundamental analysis is of no use. The third form is "strong" form asserts that all information is fully reflected in securities prices. In other words, even insider information is of no use. Estimated ANN models in this study provide valuable information about weekly direction of BIST100 index return. As an average integrated use of the three models provides 66.63% correct prediction for the direction of returns. This means that if an investor determines his/her weekly buying-selling strategy according to the prediction of the integrated ANN models, his/her weekly investment strategy will be profitable 66.63% of the time in the long run.



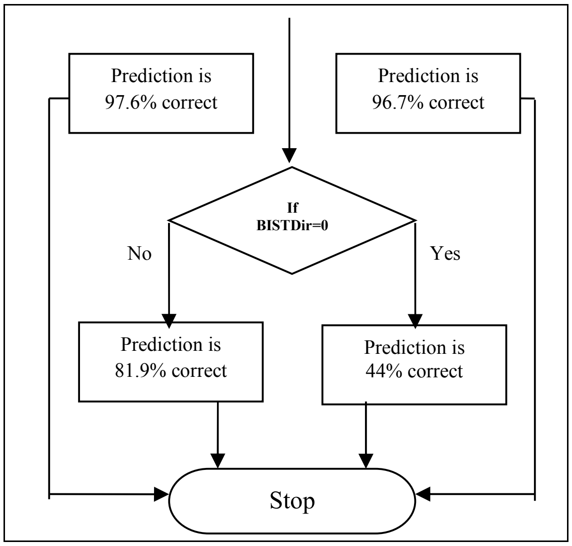


Figure 1. Flowchart of using the three combined models for prediction

4. Conclusion

This study combined three ANN models. Composite use of ANN models provides valuable information about weekly direction of BIST100 index return given the information of present BIST100 index return. Results of the study indicate that BIST100 returns follow a specific pattern in time. Generally positive returns follow positive returns and negative returns follow negative returns. Model (1) is used when present return is positive, Model (0) is used when the present return is negative and Model (0,1) is used when the prediction of previous two models are not accurate. Composite use of ANN models provides valuable information about weekly direction of BIST100 index return given the information of present BIST100 index return.

Similar further analysis can be performed for the returns of individual common stocks. This study uses weekly returns because of data availability restrictions. Further similar analysis can also be performed by considering returns of smaller time intervals, such as an intraday hourly change if the researchers can obtain available data. Hence, using small time intervals may provide more information.

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