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Prediction of the outputs of real world systems with accuracy and high speed is crucial in financial analysis due to its effects on worldwide economics. Because the inputs of the financial systems are time-varying functions, the development of algorithms and methods for modeling such systems cannot be neglected. The most appropriate forecasting model for the ISE national-100 index was investigated. Box-Jenkins autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) are considered by using several evaluations. Results showed that the ANN model with linear architecture better fits the candidate data.

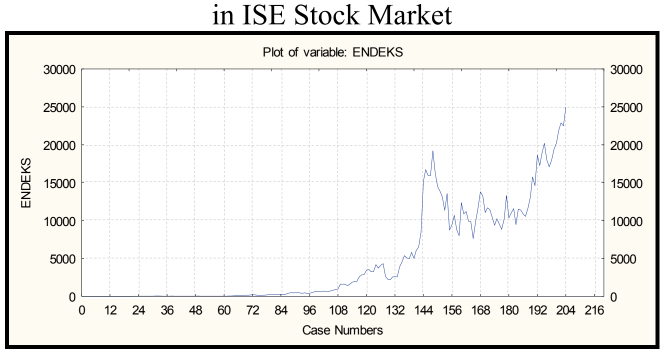
Key words: ISE stock market, time series modeling, artificial neural network, forecasting.

Introduction

Statistical modeling via artificial neural networks (ANN) has recently been widely used for time series forecasting for economy, hydrology, electricity, tourism, etc. Many studies in the literature support that ANN time series models show better results than Box-Jenkins (BJ) models (Aslanargun, 2007; Ansuj, et al., 1996; Chin & Arthur, 1996; Hill, et al., 1996; Kohzadi, et al., 1996; Maier & Dandy, 1996).

In this article, ANN forecasting models are used to study an economical forecasting problem, the case selected is from the Turkey Istanbul Stock Market. The performance of the determined model is demonstrated by comparing the models via mean square error. The aim of this study is to construct ANN forecasting models for the Istanbul Stock Exchange (ISE) national-100 index which has effects on much economic behavior. The time series taken at hand is shown in Figure 1.

Figure 1: The Fluctuation of Time Series in ISE Stock Market



Due to the nonlinear structure of the corresponding time series, ANN is the appropriate tool for accurate modeling. The

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designer has to decide about the number of inputs and outputs, the activation functions, the algorithm for obtaining the weights of the net, the number of hidden layers and the number of neurons inside the hidden layers. Because all combinations of choices result in different ANN models the analysis becomes complicated, therefore, simulation of the various types of neural nets is crucial. Hence, to address such decisions in this study, the intelligent problem solver (IPS) module of the STATISTICA 7.0 was used. The corresponding program allows a researcher to construct one million ANN models at a time and select the best of them; thus, 100,000 ANN models were run to obtain the appropriate one for ISE Stock Market. Additionally, standard ARIMA models were also constructed.

Methodology

Over all the forecasting methods, the artificial neural network (ANN) is the most popular method. For different tasks such as classification, clustering, regression, etc. (Bishop, 1995) different types of neural networks are available, such as feed forward, radial basis function (RBF), Kohonen self-organizing and Bayesian. Training of the neural network is accomplished based on a specific cost function as sum of the square errors. Different types of available algorithms for training the network and include, among others, back propagation, conjugate gradient, quasi-Newton and steepest-descent. The weights of the network, also called parameters of the model, can be found by taking the derivative of the cost function subject to network parameters and updating those parameters until those which minimize the cost function are identified.

Network Overview

The following five networks are indicated as the best potential networks for the data in this study (Bishop, 1995; Haykin, 1999).

Linear

Linear networks have only two layers: an input and an output layer. This type of network is best trained using a Pseudo-Inverse technique.

Multi Layer Percepteron (MLP)

MLP networks are constructed of multiple layers of computational units. Each neuron in one layer is directly connected to the neurons of the subsequent hidden layer. The frequently used activation function is the sigmoid function. Multi-layer networks use a variety of learning techniques, the most popular being back-propagation.

Radial Basis Function (RBF)

The RBF network consists of an input layer, a hidden layer of radial units and an output layer of linear units. Typically, the radial layer has exponential activation functions and the output layer has linear activation functions.

Generalized Regression Neural Networks (GRNN)

The GRNN network is a type of Bayesian network. GRNN has exactly four layers: input, a layer of radial centers, a layer of regression units, and output. This network must be trained by a clustering algorithm.

Results

ANN and ARIMA Forecasting Model Analysis

ARIMA models are analyzed by the Time Series module of STATISTICA 7.0, and ANN models are obtained by using the IPS module. First, stationary of variance is considered for analyzing the time series aspect of ARIMA models. Because this time series is not stationary, natural log transformation for this time series is applied. Moreover, different transformations are applied due to the trend effect. Later, the ARIMA $(0,1,1)(0,1,0)_{12}$ model was found to be the best because it has the less mean square error (MSE) compared to the alternatives: the summary of this model, which is significant, is shown in Table 1.

Table 1: Summary of ARIMA $(0,1,1)(0,1,0)_{12}$ Model

Transformations: ln(x),D(1),D(1) Model:(0,1,1)(0,1,0) MS Residual= 0,02903				
Parameter	Par. Value	P	Lower	Upper
$q(1)$	0.890715	0.00	0.819855	0.961575

Forecasted values calculated for the period between January 2005 and June 2005 by using ARIMA $(0,1,1)(0,1,0)_{12}$ model are shown in Table 2 along with observed values of this period.

Table 2: Forecasting Values for ARIMA $(0,1,1)(0,1,0)_{12}$ Model

Period	Month-Year	Forecasting Values $(\hat{y})$	Observed Values (y)
205	January-2005	25946.05	27330.35
206	February-2005	26958.43	28396.17
207	March-2005	28010.31	25557.76
208	April-2005	29103.24	23591.64
209	May-2005	30238.82	25236.48
210	June-2005	31418.70	26957.32

The MSE is calculated by using forecasted and observed values in Table 2 as follows:

$$MSE = \frac{1}{6}\sum_{i=1}^{6}\left(y_i - \hat{y}_i\right)^2 = 14217239.31\,. \quad (1)$$

After calculating the MSE for the ARIMA model, the design of the ANN time series is prepared. The time series is in month periods, hence 12 inputs are taken and regarded for the months of a year and one output neuron is taken as the design of the neural net. The values of the first input neuron called X_1 is taken for the period January 1988 – December 2003, the second input neuron is one month delayed and so its period runs from February 1988 – January 2004. The remaining input neurons are constructed in similarly. The output neuron, Y, is the values of the period from January 1989 – December 2004.

Statistical modeling using ANN is analyzed by IPS. IPS provides the opportunity to conduct various experiments through different combinations of algorithms and designs. In this research study, the IPS was ordered to choose the 5 best models among 1,000 various neural nets. The minimum input number was 1 and the maximum input number was specified as 12. The models obtained from the IPS and their performance measures are shown in Tables 3 and 4.

Table 3: Summary of 5 Best Models for Forecasting

Profile	Train Error
Linear 2:2-1:1	0.045627
MLP s3 3:9-1-1:1	0.050194
GRNN 5:5-92-2-1:1	0.000030
GRNN 7:7-92-2-1:1	0.000026
RBF s6 12:72-16-1:1	0.000027

Table 4: Summary of 5 Best Models for Forecasting (continued)

Profile	Test Error	Training/ Members
Linear 2:2-1:1	0.058281	PI
MLP s3 3:9-1-1:1	0.077745	BP100, CG20, CG11b
GRNN 5:5-92-2-1:1	0.000043	SS
GRNN 7:7-92-2-1:1	0.000041	SS
RBF s6 12:72-16-1:1	0.000037	KM, KN, PI

The Generalized Regression neural network (GRNN), Multilayer Percepteron (MLP), Radial Basis Neural Network (RBF) and Linear neural networks performed well and produced the best results among all the predicted ANN time series models. In order to obtain a more accurate forecasting model, each model was used to calculate the forecast values by running the net again for the remaining test data and the MSE was calculated for each model respectively; results are shown in Table 5.

As apparent in Table 4, the ANN forecasting model consisting of linear neural net performs the forecasting with less error. It is concluded that, for fluctuation in the ISE stock market, the usage of Linear Neural Net Time Series provides more accurate results than the other variations of the ANN time series models. The weights (parameters) of this Linear 2:2-1:1 Neural Network are shown in Table 6.

Table 5: Mean Square Errors of the Best 5 Models

Model	MSE
Linear 2:2-1:1	3468672
MLP s3 3:9-1-1:1	14388771
GRNN 5:5-92-2-1:1	4124962
GRNN 7:7-92-2-1:1	4021692
RBF s6 12:72-16-1:1	15886195

Table 6: Weights of the Linear 2:2-1:1 Neural Network

	2.1
Thresh	-0,002914
1.1	0,147587
1.2	0,762368

For modeling, monthly index values have been taken from final quotations of the Istanbul Stock Exchange National-100 index between January 1988 and December 2004. Forecasting was done for a period between January 2005 and June 2005. The best models were determined by using the Box-Jenkins method and artificial neural networks for a time series which consisted of Istanbul Stock Exchange National-100 index values. Forecasting values for considered models of both methods are provided in Table 7.

Table 7: Forecasting Values for ANN and ARIMA

Period	Month-Year	Forecasting Values (ANN)	Forecasting Values (B.J.)
205	January-2005	24837.82	25946.05
206	February-2005	27235.23	26958.43
207	March-2005	25504.51	28010.31
208	April-2005	27133.13	29103.24
209	May-2005	26053.71	30238.82
210	June-2005	27154.03	31418.70

MSE values of the models considered in Table 7 are given in Table 8.

Table 8: Mean Square Errors for ANN and ARIMA

Model	MSE
Linear 2:2-1:1	3468672
ARIMA $(0,1,1)(0,1,0)_{12}$	14217239

Table 7 shows that MSE value which belongs to the Linear 2:2-1:1 model is smaller than the MSE value of the ARIMA $(0,1,1)(0,1,0)_{12}$ model which was found using BJ method.

Conclusion

This study presented ANN forecasting models that can be used as tools for predicting unexpected booms in the economy. The corresponding analyses were conducted by using IPS because it gives an opportunity to compare various types of ANN models together. Experimental studies were performed across 1,000 neural nets and the best 5 ANN models based on mean square error were evaluated. Additionally, ARIMA models were considered in order to evaluate the effectiveness of the presented ANN models. Finally, it was expressed that an ANN model conducted with linear architecture had better forecasting performance compared to the ARIMA model.

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