Forecasting the Istanbul Stock Exchange National 100 Index Using an Artificial Neural Network

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Abstract—Many studies have shown that Artificial Neural Networks (ANN) have been widely used for forecasting financial markets, because of many financial and economic variables are non-linear, and an ANN can model flexible linear or non-linear relationship among variables.

The purpose of the study was to employ an ANN models to predict the direction of the Istanbul Stock Exchange National 100 Indices (ISE National-100).

As a result of this study, the model forecast the direction of the ISE National-100 to an accuracy of 74, 51%.

Keywords—Artificial Neural Networks, Istanbul Stock Exchange, Non-linear Modeling.

I. INTRODUCTION

THE stock market has been one of the most popular investments owing to its high returns. On the other hand, there is some risk to investment in the stock market due to its unpredictable behaviors. Thus, an 'intelligent' prediction model for stock market forecasting would be deeply desirable and would of wider interest. Artificial Neural Networks (ANNs) are relatively recent method for business forecasting. The success of ANN applications can be qualified of their features and powerful pattern recognitions capability. ANNs have been successfully applied to wide range of forecasting problems such as bankruptcy, business failure, exchange rate, interest rate, future prices, stock return, stock market index, and many others [1],[2],[3].

For this reason the purpose of this study is to employ Artificial Neural Networks models to predict the direction of the Istanbul Stock Exchange National 100 Index.

To realize this purpose the study is organized as follows. The next section describes the results of earlier research. This section followed by the research restriction, data, research methodology and discussions of the empirical findings. The study closes up with conclusion.

Several studies relating to a comparison of artificial neural network (ANN) and statistical models have been conducted in the literature. For instance, multiple discriminate analyses and the ANN method were used to predict the performance of shares; the true presumption percentage being 74% for discriminate analysis and 91% for ANN [4]. Both linear and nonlinear models were used to predict stock returns by [5] who emphasize the Nonlinear Model proving to be more effective. Such studies prove that the nonlinear model presents more consistent results for stock exchange market. For this reason, ANN applications have been widely used in a variety of areas in financial markets [6],[7],[8],[9]. Reference [9] confirmed that ANN was used for the solution of numerous financial problems. References [10],[11],[12] emphasized that ANN could be used in the prediction of financial markets, in particular, the prediction of stock market indexes which are considered to be a barometer of the markets in many countries. For this reason, ANN Models have widely appeared in literature in the prediction of stock market index in different countries.

Reference [12] used the ANN Model in Singapore to predict the direction of the stock exchange market and they estimated the direction of the following day as 81%. The study used the Back-propagation Method of Artificial Neural Network Models to predict the direction of Istanbul Stock Exchange Market 100 index, and estimated the direction the following day as 60, 81 % [14]. Reference [15] used ANN and Regression Models for the prediction of Istanbul Stock Exchange Market index through weekly and monthly datum. They reported the prediction success of ANN on daily, weekly and monthly datum as 57.8 %, 67.1 %, and 78, 3 %, respectively.

II. DATA

The input variables were; the highest and lowest prices paid during the day, the closing price, the exchange rate (as the U.S dollar), and response rates. The output variable used in this study was prepared according to the direction of the index on the following day. When the index increased, the rate was considered as 1, while when the index decreased, the rate was considered as 0.

For the purposes of this study, all data relating to an index (the highest and lowest prices paid during the day, and the closing price) was obtained from the Istanbul Stock Exchange

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Market. Macro economic data (with the exchange rate as "U.S dollar" repose rates) was obtained from the Central Bank of the Republic of Turkey.

The data was divided into two sets, the training set and the test set. 1805 observation were used for the training of the network while the rest of the 100 data was used for testing. The Model was analyzed with the Think Pro Networks for Windows software packet.

III. METHOD

The Artificial neural network best described as a hierarchic organization forming interactions between a number of simple elements connected in parallel to world objects, in much the same way as a biological neural system is connected. There are three components forming the structure of an artificial neural network, namely a neuron, connections, and weights. The basis of the artificial neural network is the artificial neuron, much like that employed in biological neural networks. The artificial neuron is basic process element of a network, with all neurons in the network receiving one or more pieces of input and producing only one output. This output may be excluded from the artificial neural network, or may be reused as input for other neurons.
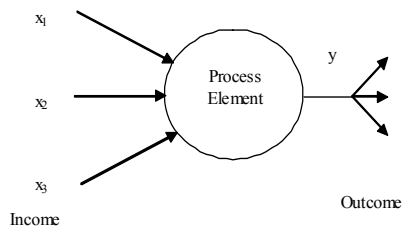

Fig. 1 Artificial Neuron

The connection of artificial neurons to each other in parallel forms the artificial neural network. Layers are formed in the same direction by the connection of neurons.

Different network architectures are formed by the connection of layers to each other in different ways. The first layer in the artificial neural network is the input layer which helps to accept external data into the artificial neural network.

The other layer is the output layer, which relays the information out. When another layer appears between the input and output layers, it is called a hidden layer. One of the most important components in artificial neural networks is connections. Through these connections, data transformation to other connections is facilitated, with each having a weight showing the relative force (mathematical coefficient) of datum to be used as input in a neuron. Every connection providing this input transformation function among the neurons has a different weight. Thus, the weights have an effect on each input of each process component.
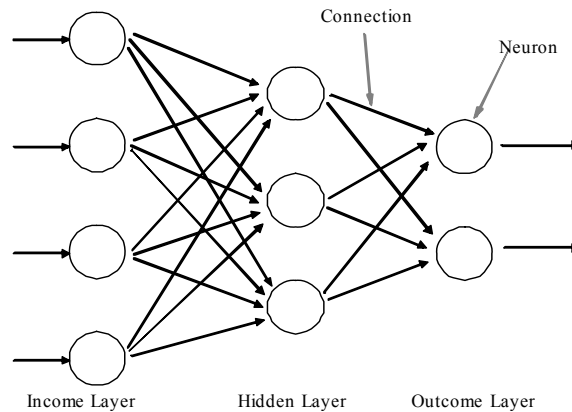

Fig. 2 Model of Artificial Neural Network

Upon examination of processing in an artificial neural network, it can be seen that input enters the network via the input layer, and is then transported from one neuron to another by being processed in each neuron until reaching the output layer. This transportation is achieved via connections. Both training algorithms, used to alter weights, and the neuron's two functions play important roles in the appearance of training ability and the processing of the artificial neural network. The facility for processing data from a neuron is realized by two functions; total function and transfer function (Fig. 3).
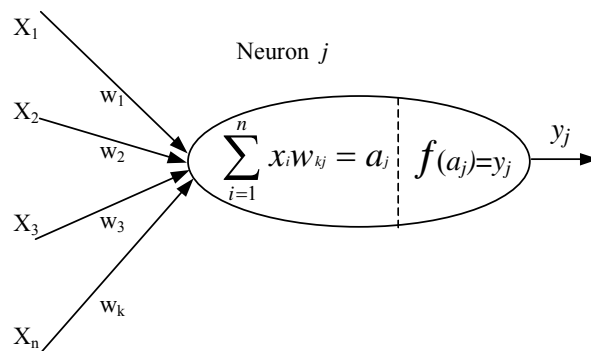

Fig. 3 Total and Transfer Function

The duty of total and transfer function is to take the weighted sum of all inputs entering the neuron. For this reason, the number of input (x_i) belonging to the neuron (j) and the weights (w_{kj}) of the input are multiplied and the total (a_j) is calculated.

$$\sum_{i=1}^{n} x_i . w_{kj} = a_j$$

(1)

This total forms the total weighted stimulus entering the neuron, and is processed by the transfer function. Total function is composed of different values. Total function is also the function which decides to what degree a neuron will be

stimulated. An output is produced (y_j) depending on the level of stimulation the neuron receives, with the relationship of the stimulation level to the output determined by the transfer function.

$$f(a_j)=y_j \qquad (2)$$

There are three main steps in the training process of an artificial neural network.

  i. Calculation of outputs

  ii. Comparison of outputs to target outputs, followed by calculation of error.

  iii.   Repetition of the process by changing the weights.

x_{ij}= inputs
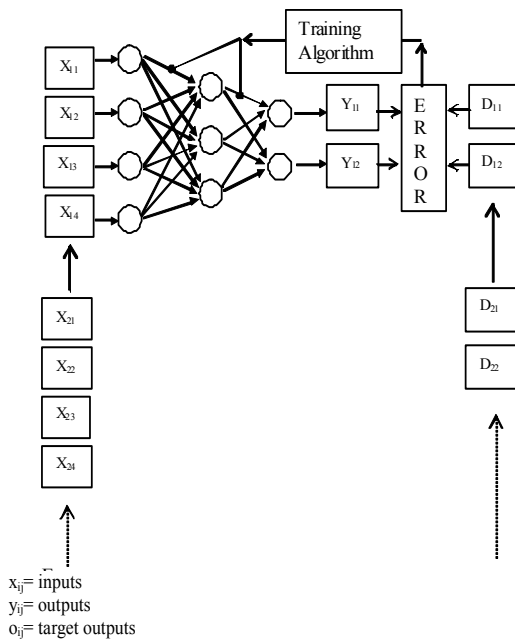y_{ij}= outputs
o_{ij}= target outputs

Fig. 4 Training Process and Training Algorithm

Data and results used in the system relate to a problem in the real world, or put another way; examples are used in the training process of the artificial neural network. Variables related to the problem form the input series, the results of which form the target output series that the artificial neural network must attain. The parameter, which determines the relationship between the input and output in the education set, is what the artificial neural network is expected to learn. The aim of the exercise is to organize the weights of the artificial neural network in such a way so as to produce the correct output series for all the input series. It can also be considered as organization of the coefficients of the inputs entering the neuron. Thus, the artificial neural network represents a parameter in the real world depending on the inputs and outputs employed.

Feed-forward, back-propagation architecture was developed in the early 1970s by several independent sources. The Back-propagation Algorithm, or Extended Delta Algorithm, is

probably the primarily used training algorithm. Error is considered as a function of the weights in the network, with the mean of the errors' squares minimized by employing the Gradient Descent Method, as can be witnessed in the Delta Algorithm. In fact, the Back-propagation Algorithm is a form of a momentum term added to the Delta Algorithm. The momentum term helps us to deduce the minimum error points and arrange the direction. In addition, as in the Delta Algorithm, the network is prevented by Momentum Term from finding a false result by causing it to become stuck on some local cavities. On the other hand, we shouldn't rely on a large obstruction always being hindered by the system from reaching a correct conclusion. The most common form of the Back-propagation Algorithm, with several variations, is a momentum term added to a Delta Algorithm.

$$\Delta w_{ij}^{(t)} = \alpha . \delta_j^{(t-1)} . x_k^{(t-1)} + \mu \, \Delta \, w_{ij}^{(t-1)} \qquad (3)$$

w_{jj}, the weight from neuron u_j to neuron u_i, is called a α "learning rate" or "learning coefficient"
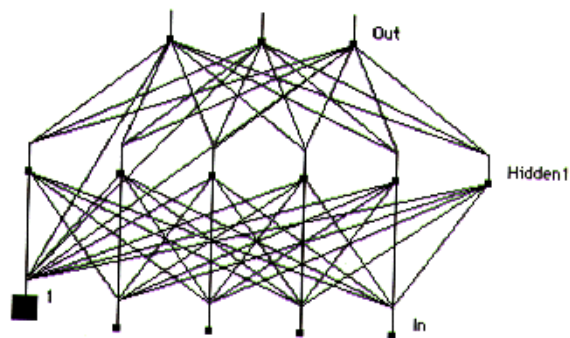

Fig. 5 An example Feed-forward Back-propagation Network

IV. Empirical Findings

The Think Pro- Neural Networks for Windows package was used to proceed the Model of the Artificial Neuron Network[1]. This program was preferred because it maintains several architectures, training rules, and transfer functions for development of the Artificial Neuron Network Model. One of the most important functions of this program is to show the performance of the network developed during the training period, according to the test data and network error calculated simultaneously as graphics. Thus, it is easy to observe whether the data has been memorized by the network or not.

Firstly, the architecture of the artificial neuron network to be constructed, the training rules to be used, the manner in which the error is to be calculated, the number of neurons in the input and output layers, the number of hidden layers, the

training coefficient related to the training algorithm and the transfer function in layers, and the momentum term were chosen, and the artificial neuron network was thus structured.

A testing period to find a suitable model for the problem area is observable due to the lack of methodologies for use in the development of an Artificial Neuron Network Model. An intuitive Approach is needed for the architecture in order to develop a suitable model and develop parameters relating to the training statute. Several ineffective models were developed until finally finding an effective model in the prediction of Istanbul Stock Exchange Market 100 Index. Training was not realized in some of the ineffective models, with a resulting failure to decrease the percentage of the error in the network. In some cases, the network memorized the data, resulting in an observable tendency to decrease the percentage of error in the training data, while increasing the percentage of error in the test data. All ineffective models were eliminated, and as a result, the model, parameters given below, found the training data to be 74.52 % in 1684 iteration.

TABLE I
PARAMETERS RELATED TO THE ARTIFICIAL NEURON NETWORK

Architecture	Multilayer Full Feed Forward		
Error Type	Mean Squire Error		
Iteration	1684		
Training Set Error	0,6452		
Training Set Classification	58,37% correct		
Test Test Error	1,5048		
Test Test Classification	74,51% correct		
	Input	Hidden Layer-1	Output
Nodes	50	1	1
Max Nodes	50	10	1
Rule		Back Propagation	Back Propagation
Input Function	Mean / SD		
Transfer Function		Linear	Threshold Linear

***"Correct" Classification: All outputs are within tolerance of desired outputs, tolerance = 0,499

V. CONCLUSION

Traditional methods based on linear models have failed to track the strongly non-linear dynamics of financial markets in the present day, and have fail to model the structure of financial market behavior.

In this study, we have presented an approach that utilizes ANN techniques to forecast the direction of the ISE National-100. For this purpose, we developed an efficient three-layer neural network with revised Back propagation algorithms to forecast the ISE National-100. As a result, the following day direction of the index was predicted to an accuracy of 74, 51% which shows that ANN technology has the potential for modeling the market behavior.

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