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PREDICTION OF THE FINANCIAL RETURN OF THE PAPER SECTOR WITH ARTIFICIAL NEURAL NETWORKS

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The unknown nature of the future requires us to question our decisions and seek reliable methods. The artificial neural networks approach, which is one of the methods used to best predict the future and one that is important for decision making has been thought of, particularly in recent years, as a method with a high level of validity in the fields of economy and financial prediction. The Istanbul Stock Exchange (ISE), at which millions of national and international investors operate, is among the developed stock exchanges of the world. The ISE has the attributes of being appropriate for making predictions regarding financial returns, without any sector differentiation, as a whole. In this study, it was aimed to predict monthly stock yields of 14 different paper companies dealing with the ISE (Istanbul Stock Exchange) by using artificial neural network. Four different variables (the gold price, ISE daily trading volume, exchange rate purchase-sale average, and monthly deposit interest rates by utilizing) and 127 months data were used. Results show that the monthly stock yields of the paper sector can be predicted correctly to account for 95% of the variability of data with the artificial neural network model, and the average absolute percentage failure value was 6.85%.

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INTRODUCTION

The fact that there are no methods capable of determining the behaviour of equity prices with a high level of certainty results in the investment field bearing more risks than many others (Kutlu and Badur 2009). The most researched issues in financial circles are led by the foreseeability of equity returns regarding the investor who desires to see the future more clearly. The technical analysis, which finds a spread application area in practice, leans on the principle that the information regarding the future price of equities is hidden in the past prices (Murphy 1999; Kirkpatrick II and Dahlguist 2007). But these utilized traditional methods are partially unsuccessful due to the non-linear and complex behaviours of equity prices. The artificial neural network method is a field that provides us with successful results, as it has done it many other areas (Kutlu and Badur 2009).

An artificial neural network (ANN) is an artificial intelligence technology that generates successful results in cases involving multiple variables and at which complex,

mutual interactions exist between the variables or where no single solution set is available. Due to these features, the artificial neural network can be used in many fields.

The ANN has an algorithm that has the capability to learn and make decisions during the process (Ataman 1999). The unknown and hard-to-determine relations between the input and output can be revealed without any assumptions or preliminary information from the ANN. The ANN, different from linear models, can also provide modelling in cases where the relations between the data of the handled problem is not linear, is uncertain, and may be indefinite (Zhang et al. 1998).

ANNs consist of artificial neurons, which are parallel and connected consecutively to each other, and information with different weight values conducting connections, which affect the input of the neurons (Yildiz 2001; Demir et al. 1999). The data processing is performed by the conversion of the information that arrives at the network into output by utilizing these weighted connections. This structure increases the fast data processing capability of the ANN, ensures that it performs complex processes by operating simultaneously.

ANN has found wide application areas in the modelling and monitoring of complex systems due to its ability to learn, generalize, perform parallel processes and tolerate failures, and its superior qualities such as capability to present easy solutions to non-linear complex problems, which are difficult to model (Sagiroglu 2003; Atik 2004; Haykin 1994; Skapura 1995). To develop this calculating and data processing power is rather difficult or not possible with traditional programming methods (Oztemel 2006).

The development of artificial intelligence technologies has allowed these technologies to be used in diverse areas. Among these technologies, which also find application in the field of accounting-finance, the artificial neural networks in particular are being used successfully to forecast financial failure. The artificial neural networks, which have transferred the learning ability of humans from their experiences into the computer environment, can imitate the functioning principles of the human brain (Nabiyev 2003).

One of the first performed studies abroad with artificial neural networks on stock exchanges in the field of finance was the study by Kimoto et al. in 1990 on the Nikkei Index in Tokyo. Later, Kamijo and Tanikawa (1990) used the repeating neural networks and Ahmadi (1990) the backprop (backpropagation) network. Yoon and Swales (1991) have worked both with quantitative and qualitative data. Choi et al. (1995) predicted the daily direction changes of the S&P 500 index.

Bambang et al. (2000) used the feed-forward and backprop algorithm for the equities of the Indonesian stock exchange on four months worth of data. Kutsurelis (1998) used the artificial neural network and multiple linear regression analysis of the traditional prediction methods in trend predictions of the stock index in his dissertation and determined that the artificial neural systems provided better results.

Yao and Poh (1995), in their study, evaluated the Malayan Kuala Lumpur Stock Exchange index via artificial neural networks with applied different backprop. As a result of these predictions, they gained significant profits on paper. Beyond this, experience has shown that useful predictions can also be made without wide market data or information usage.

In Turkey, artificial neural networks are used primarily in foreseeing financial failure (Yildiz 2001). In some studies in recent years, it has been determined that artificial neural networks provided better results than linear and logical regression models on estimating the direction of the equity index (Diler 2003; Altay and Satman 2005; Senol and Ozturan 2008). Although there are studies on the prediction of stock exchange indexes, the scarcity of such studies in Turkey has drawn some attention. Yumlu et al. (2004) found in their research on financial data of 12 years that the artificial neural network model showed a better performance than the autoregressive models. Yıldız et al. (2008) have predicted how the ISE index will change its direction in the coming days with a correctness of 74.51% by utilizing an artificial neural network. Egeli et al. (2003) used the artificial neural network and moving average method in the prediction of the ISE index and found that the artificial neural network models provide better predictions.

Kucukkocaoglu et al. (1997) attempted to predict the differentiation between companies making use of financial information manipulation and those that do not by the artificial neural network model. The results obtained by the study showed that the probability that the prediction was right is at 86.17%, whereas the probability of a false classification was 13.83%.

Akkoç (2007) made an application on companies subject to the Capital Markets Board and traded at the ISE in order to foresee financial failure one year in advance with the neural fuzzy network model, and at the same time, in order to compare the performance of the neural fuzzy network model, they applied multiple differentiation analysis and the artificial neural network model to the same sample. In order to be able to realize these predictions, the financial margins of the companies were utilized, and as a result of the prediction study on 142 companies, results regarded as successful were obtained from all three of the developed models. Whilst the success of the artificial neural network at separating the companies into the correct groups was determined to be 86.1%, this ratio was determined as 83.3% with the multiple differentiation analysis, and the success of the neural fuzzy network model at assigning the companies to the correct groups was determined as 80.6%. In addition, it was determined that there was no meaningful difference between the classification successes of the established models.

Vural (2007) made a financial prediction study with artificial neural networks and obtained rather successful results by estimating the daily closing index with an average failure of 3% and with index values, a failure of about 1%.

Yurtsever (2006) performed the ISE index prediction with the artificial neural networks methodology and the linear regression model. As a result, the artificial neural network model, established with a non-linear architectural structure, provided more efficient results for explaining the index.

Akel and Bayramoğlu (2008) developed a multi-layered artificial neural network model in order to perform a forecast of the ISE index by utilizing some basic macro-economic indicators in February 2001 in Turkey, which was at that time a financial crisis environment. It is seen that the model generated a signal with a correctness ratio of 73.68% regarding whether the index will show a decrease or increase compared with the previous day.

Some of the other studies in order to prediction the return quantity of financial investment tools in the market or the index values with artificial neural networks can be

listed as (Vural 2007): prediction of equity values (Schoeneburg 1990), prediction of future markets values (Grudnitski and Osburn 1993), prediction of monthly equity movements (Li 1994), equity market prediction (Kimoto et al. 1990), and testing of the market efficiency – prediction of equity returns (Wong et al. 1995). The target of these mentioned studies was based on the previous equity values and the respective financial ratio in estimating the equity values of one or more days later. Looking at the previous performed artificial neural network studies in the equity market, it can be seen that nearly all studies were realized by utilizing different data models.

The ISE is among the developed stock exchanges of the world and has the characteristics of being a stock exchange, which increasingly attracts the attention of national and international investors. It cannot be said that the analysis at the subsector level by utilizing artificial neural networks is performed sufficiently qualitatively at the ISE, which covers many sectors within it. The paper sector has a structure which has a financially strong construct and is in interaction with many different sectors. Correct return prediction in this field will both effect individual investors and influence the other sectors. In this study, the monthly return forecast of the paper sector, which is represented by 14 companies at the ISE, is examined by the artificial neural networks method. Certain information regarding the paper sector in Turkey is given in Table 1 (FAO 2011).

Table 1. Information Regarding the Paper Sector in Turkey

Years	Production (Tons)	Import (Tons)	Export (Tons)	Consumption (Tons)
2000	2.805.000	1.402.540	66.000	4.141.540
2001	2.651.000	1.037.000	164.000	3.524.000
2002	2.937.000	1.621.000	179.208	4.378.792
2003	2.937.000	1.622.470	179.208	4.380.262
2004	2.937.000	1.629.000	179.208	4.386.792
2005	2.937.000	2.604.961	179.208	5.362.753
2006	2.797.000	2.613.118	179.208	5.230.910
2007	2.787.000	3.123.470	205.110	5.705.360
2008	5.576.000	2.911.001	323.723	8.163.278
2009	5.567.000	2.889.991	264.096	8.192.895

In this study, it was aimed to predict monthly stock yields of paper sectors dealing with the ISE (Istanbul Stock Exchange), according to four different variables (the gold price, ISE daily trading volume, exchange rate purchase-sale average, and monthly deposit interest rates by utilizing) by using artificial neural networks and compared with multiple linear regression models. These variables have been found frequently in the literature. Also, complete records of these variables could be obtained.

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EXPERIMENTAL

Materials

In Turkey, studies regarding the prediction of financial failure, direction of the stock exchange, and bankruptcies are preferred, and stock exchange index predictions are not performed that much. Such predictions are handled more in foreign-sourced studies. With this study, predictions covering a period of one year of the USD ($) based monthly composite return ratio of the paper sector by 14 companies, traded at the ISE, are performed.

In the study, data of 127 months between June 1st 2000 and December 31st 2010, obtained from the internet sites of the Electronic Data Distribution System of the Turkish National Bank (EDDS 2011) and Istanbul Stock Exchange (ISE 2011), are used. 14 paper companies' primary products are corrugated cardboard boxes, printing and writing paper, newsprint, cleaning paper, paper, and cardboard.

Methods

The main reason for the importance of forecast modelling in the fields of economy and finance is that it plays an important role in the decision mechanism. Simply, good forecasts allow good decisions. This in turn highlights how important it is to obtain better forecasts.

In the prediction of the next 12 months return of the paper sector, feed-forward, backprop, multi-layered artificial neural networks are preferred and testing is performed by the Matlab package software (Demuth and Beale 2000). In addition to this, prediction results, obtained with artificial neural networks, are compared with the results obtained with the multiple linear regression models.

Multiple linear regression is a method used to model the linear relationship between a dependent variable and one or more independent variables. The dependent variable is sometimes also called the predictand, and the independent variables the predictors. Multiple linear regression is based on least squares: the model is fit such that the sum-of-squares of differences of observed and predicted values is minimized. Multiple linear regression is calculated with the Eq. 1.

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \varepsilon \qquad (1)$$

where Y indicates dependent variable, X_i indicates independent variables, β_i indicates predicted parameters, and ε is the error term (Kalaycı 2009).

Artificial Neural Networks

The artificial neural cell, which is generated by modelling biological neural cells and has a much more simple structure compared with them, is the smallest data processing unit, which constitutes the base for the operation of the ANN. The basic neural cell model can be seen in Fig. 1. In the artificial neuron, there are mainly inputs, weights, addition function, activation function and outputs (Koca 2006).
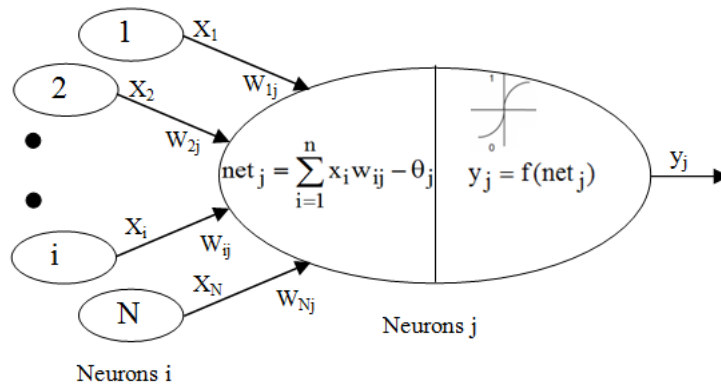
Fig. 1. Artificial neural cell (artificial neuron)

Inputs (x_i) are data, obtained from the external environment or the other artificial neurons. The quantitites (w_{ij}) indicate the effect of a data that arrives at a artificial neural cell on that cell (Oztemel 2006). The addition function (threshold function) (net_j) is a function that calculates the net input coming to the cell. And the activation function (f) is a function which processes the net input obtained from the addition function and is calculated with Eq. 2, meaning the activation potential (net_j), and determines the output (y_j), calculated with Eq. 3, which will be generated by the cell in response to this input (Sagiroglu et al. 2003).

In the cell models, there may be a bias with +1 value increasing the net input or polarization threshold input (θ_j), with -1 value decreasing the net input,

$$net_j = \sum_{i=1}^{n} x_i w_{ij} - \theta_i \qquad (2)$$

where x_i indicates the i. input, w_{ij} the connection weight from j. element to i. element, and θ_j the polarization value (negative of the threshold value), and n indicates the (input signal sending) artificial neuron number in the previous layer.

The artificial neuron output value, which depends on the selected activation function if the sigmoid function should be used as the activation function, is calculated with Eq. 3. The generated output is sent via the connections of the network to the other cells (Sagiroglu et al. 2003; Oztemel 2006).

$$y_j = f(net_j) = \frac{1}{1 + e^{-net_j}} \qquad (3)$$

The activation (transfer) function normalizes the activation potential of an artificial neuron and it limits between the desired values (mostly [0.1] or [-1.1]) and also provides the ANN converges. The activation function derivative should be obtainable and continuous (Oztemel 2006; Goktepe et al. 2005).

When more than one parallel processing artificial neuron is needed, multi-layered network structures are necessary. In Fig. 2, a three layered network structure, artificial neurons, and inter-layer relations are shown schematically (Oztemel 2006).

In the structure of a multi-layered ANN, there are mainly three layers, consisting of an input layer with artificial neural cells, which are connected to each other in different ways, an output layer and a hidden layer (intermediate layer). The input layer is the first layer and is responsible for receiving in-coming data to the ANN and to deliver these to the intermediate layer. The hidden layer processes the information, coming from the input layer, and sends these to the output layer. The neurons in the hidden layer do not have any connection to the external environment. The output layer processes the information coming from the intermediate layer and generates the output to be generated for the input set (samples) presented by the input layer of the network, and sends these to the outer world (Oztemel 2006; Benli 2002).
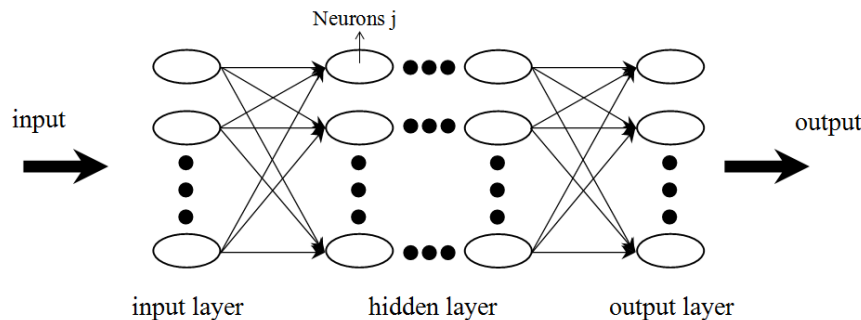

Fig. 2. Sample of a multi-layered artificial neural network

Artificial neural networks with feed-forward are structures in which the artificial neurons are separated into intermediate layers and information is conducted from the input layer towards the output layer via single directional connections. The most popular of such networks in which there are no connections between the artificial neurons in the same layer and in which the neurons in each layer are fed only by the artificial neurons of the previous layer are multi-layered perceptrons (MLP). Since these networks can generate solutions to very different problems, they are used widely and successfully in applied science and engineering problems (Schmoldt et al. 2000).

The number of artificial neurons in the input layer is equal to the data input number of the ANN, and the number of artificial neurons in the output layer is equal to the number of data to be obtained from the ANN. And the numbers of the hidden layers and the artificial neurons in the hidden layers are commonly determined by the trial-and-error method (Atik 2004). Also, the learning algorithm, activation function, learning and momentum coefficients, the start values of threshold values are important for determining the most appropriate network architecture (Cointe and Rouger 2005).

Networks with small numbers of artificial neurons in the input layer and the hidden layer can only perform linear forecasting; they cannot differentiate complex patterns. The increase in the number of artificial neurons in the input layer and the hidden layer extends the duration for the training of the network and prevents the networks from

performing a generalization (Haykin 1994; Chaudhuri and Bhattacharya 2000; Guler and Ubeyli 2006).

The backprop algorithm (backpropagation) is a basic learning algorithm that is widely used in the training of multi-layered artificial neural networks. The backprop algorithm, which performs the processes in two stages, spreading and adaptation, requires a multi-layered network structure with feed-forward and training under supervision. It is often preferred because it is easy to comprehend, gives efficient results, and is mathematically easily provable (Altun et al. 1999; Topcu et al. 2006).

Designing artificial neural networks and selecting definite design parameters, the selection of which can be less or more subjective, is very important for achieving the best neural network performance. The information, capable of determining the performance of the network, is obtained by the aid of diverse diagnosis methods using the difference in amount between the output, calculated by the ANN, and desired output, targeted to be minimized. From the well known and widespread diagnosis tools, the root mean-squared error (RMSE) and the mean absolute percentage error (MAPE) values are calculated with parities 4 and 5 in order (Sagiroglu et al. 2003).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2}$$

(4)

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100$$

(5)

In these relationships t_i indicates the real value, td_i the model prediction value, and N the number of testing data.

RESULTS AND DISCUSSION

The artificial neural network approach, which generates consistent results with real values, can be used without the need for mathematical modelling, is used to model change in the paper sector return in relation to the variables as gold price, and is also used in ISE daily trading volume, exchange rate purchase-sale average and monthly deposit interest rates.

The sum of the consecutive data of each twelve-month period of previous years is correlated with the following month of the next year, and thus the data is organized. Seventy-three of the organized data are grouped randomly as reference data for training purposes, 15 in order to terminate the training of the network early when the generalization gets bad as validation data, and 15 in order to control the appropriateness of the generalization as test data. So, the groups are used to train the artificial neural network by establishing different data sets.

The training is performed by making attempts to establish different models with different network structures and learning parameters. The most sensitive result is aimed for by testing the models with data not used in the training set in order to test the performance of the networks.

The obtained predicted values as a result of the testing process are compared with the real values. The model providing the best prediction values with respect to the root mean-squared error (RMSE) ratio, calculated with Eq. 4, and the mean absolute percentage error (MAPE) ratio, calculated with Eq. 5, is chosen as the prediction model.

In Fig. 3, the ANN model, consisting of one input layer, two hidden layers, and one output layer, which provided the results that are closest to the real values, is shown. In the model, the variables gold price, ISE daily trading volume, exchange rate purchase-sale average and monthly deposit interest rates and paper sector return are taken as the output variable. The processing element (neuron) numbers in the hidden layers are, in order, four and ten.
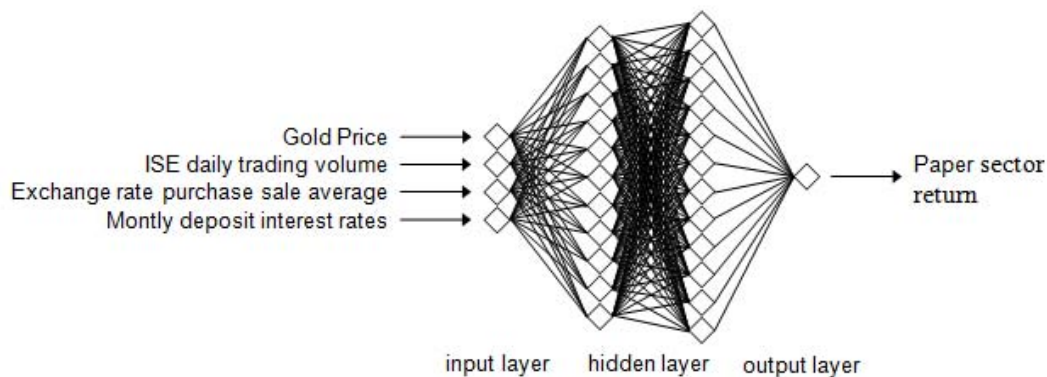

Fig. 3. Architecture of the ANN, selected as the prediction model regarding the paper sector return

In the solution of the problem, a multi-layered ANN with feed-forward and backprop is preferred, and the training and try-out is performed with Matlab package software. In this study, the hyperbolic tangent sigmoid function (tansig) is selected as the activation function (transfer), the Levenberg-Marquardt algorithm is selected as the training algorithm, the gradient descent momentum backprop algorithm (traingdm) is used as the training rule, and the mean-square error (MSE) is used as the performance function.

In order to provide that each parameter contributes equally to the models, the data in the training, validation, and test sets are presented to the network by normalizing these between -1 and 1, since the hyperbolic tangent sigmoid function was used in the models, and later the data are converted to original values by subjecting these to a reverse-normalization process in order to be able to interpret the results. The normalization (scaling) processes are performed with the aid of the Eq. 6. In this equation X_{norm} indicates the normalized data, X is the real value of the variable, X_{min} is the minimum value of the data group, and X_{max} is the maximum value of the data group.

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$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \tag{6}$$

It is assumed that the 0.001 targeted error value would be sufficient for the training of the artificial neural network. Along with this, it is targeted that the solution is made general by applying the "early stopping" rule in the Matlab software, with which also the errors of the validation data during the training of the network can be observed.

During the training, the mean-square errors of the data sets are tracked and as a result of the trial (epoch), in which it was observed that the error quantities of the training and validating values tend to differentiate and where the generalization was disrupted, the training is stopped and the change of the paper sector return is modelled with the obtained network parameters.

The iteration dependent error variation quantity of the selected artificial neural network can be seen from the graphic in Fig. 4, and the epoch number, at which the model training was stopped, is 17.
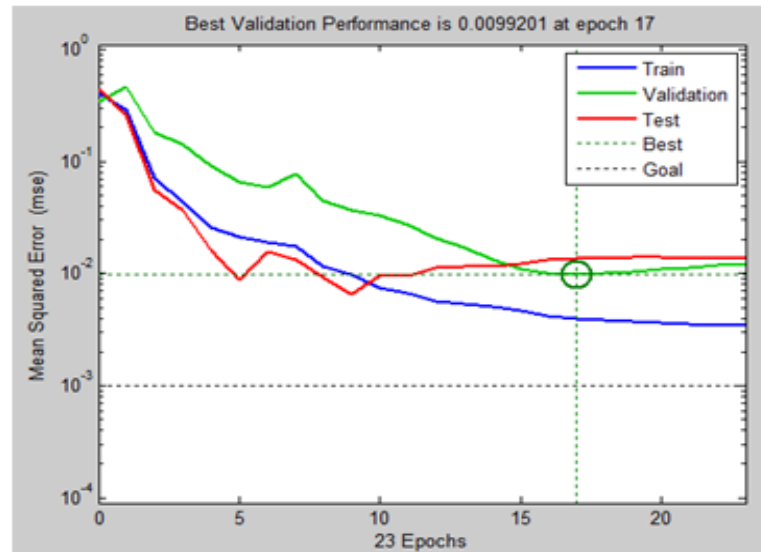
Fig. 4. Iteration dependent error variation graphic of the ANN

The relation between the values, calculated with the prediction model regarding the training, validation and test data, and the real values can be seen in Fig. 5. And the comparative graphic of these values is given in Fig. 6.

Respecting the results obtained from the validation and test set and the real result of the problem in the performance of the predictions, it is seen from the R^2 value of 95%, the MAPE value of 6.85% and the RMSE value of 0.381, that the network achieved sufficiently sensitive results.

By also applying a multiple linear regression model on the same data, it was examined which method provides better results. Equation 7 is obtained from the multiple linear regression model,
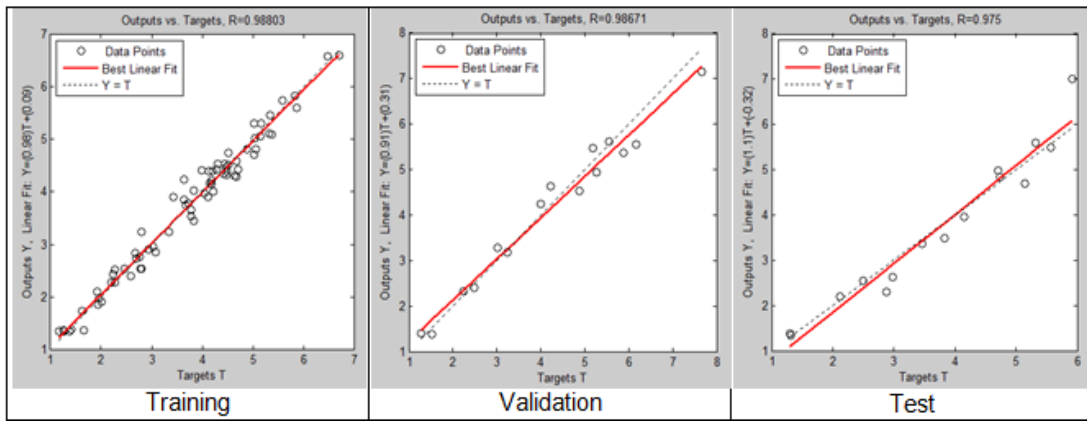
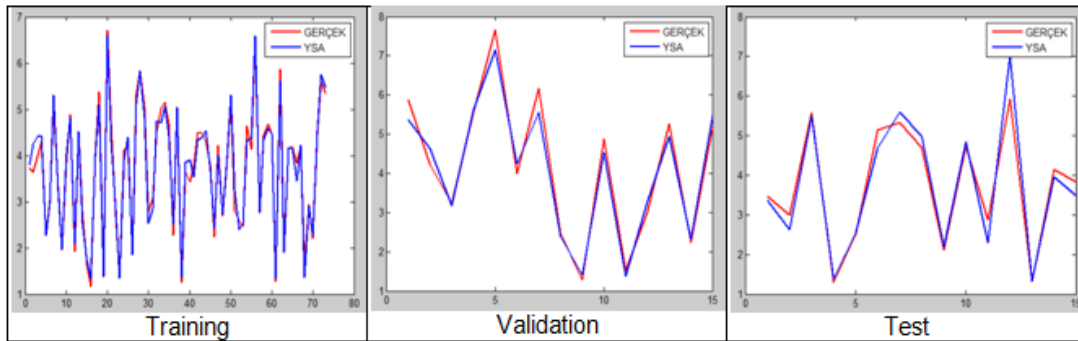**Fig. 5.** Relation between the real values and the values from the ANN

Fig. 6. Comparison of the real values and the values from the ANN

$$Y = 1.862 + 5.7689X_1 + 1.4902X_2 + 0.125X_3 - 0.003X_4 \qquad (7)$$

where Y indicates dependent variable, X_i indicates independent variables (respectively the gold price, ISE daily trading volume, exchange rate purchase-sale average, and monthly deposit interest rates), and β_i represents the estimated values of parameters.

Resulting from the regression model, the R^2 value is determined as 70%, the MAPE value as 21.83%, and the RMSE value as 0.797. These results indicate that the used models in both methods can be used for accurate predictions, since they both have a high explanatory value. Furthermore, the artificial neural networks provided better forecast results compared with the regression models. As a result of the performed variance analysis, it is determined that the test result predictions of both models, realized at a significance level of 5%, and the real values are not significantly statistically different ($p > 0.05$).

As a result of the established artificial neural network model, changes in the variables and the paper sector monthly return forecast regarding 2011 are given in Table 2, and the paper sector monthly return distribution is given in Fig. 7.

Analysing the predicted return values of the paper sector for 2011, it is foreseen that this will have a return rate of above 5% during the first three months, slightly below

4% during the following four months, and slightly above 4% during the last five months. The average return value is determined to be 4.61%.

Table 2. Variables for 2011 and Paper Sector Return Predictions

| Months	Gold Prices	ISE Trading Volume	Exchange Rate	Interest Rates	Paper Return (%)
1	2232,8162	1918712,9480	1,5505	17,5142	7,2529
2	2283,2102	2071969,4570	1,5403	16,9325	7,0497
3	2313,0394	2231047,6950	1,5280	16,7075	5,0938
4	2349,8805	2342457,6610	1,5133	16,4692	3,3569
5	2399,4241	2417289,0780	1,5036	16,2742	2,9730
6	2451,6097	2429345,4470	1,5022	16,0892	3,1553
7	2506,6437	2406775,7250	1,5047	15,9117	3,6882
8	2556,3318	2399882,5090	1,5066	15,7367	4,1079
9	2607,4826	2334425,9070	1,5085	15,5992	4,7770
10	2660,9159	2369288,2490	1,5088	15,4867	4,7744
11	2718,0527	2411053,5940	1,5051	15,2475	4,6823
12	2762,1259	2466940,0390	1,5009	15,0075	4,4808
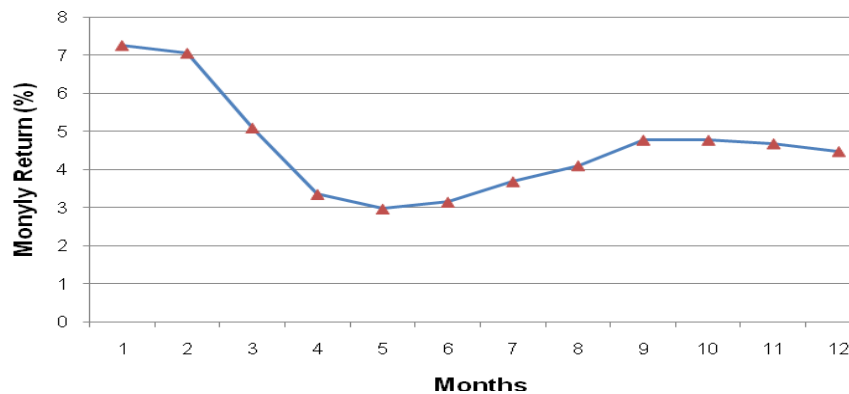
Fig. 7. Distribution of the paper sector monthly return prediction values for 2011

CONCLUSION

In the study, the annual prediction of the change of the USD ($) based monthly composite return of the paper sector, traded at the ISE, according to the gold price, ISE daily trading volume, exchange rate purchase-sale average, and monthly deposit interest rates by utilizing artificial neural networks and multiple linear regression models was performed. As a result of the realized trials, it can be seen that both methods provide very good results, but that the artificial neural network has better predictions than the multiple linear regression model.

Forecast studies with artificial neural networks show that the results are predicted with a very high success rate, though the past is not that old. It is definite that in this issue, with the advance of science and technology, different network structures and learning functions, and the development of different software, much more successful

forecasts will be possible. Also, in turn, without too much market data or information, significant profits will be achieved on paper by successful predictions. As a result of successful predictions, investors will be able to make more incisive and healthy decisions in their future oriented investment choices, as will companies in their future oriented plans. Due to the fact that forecast related studies are limited in Turkey, such studies should be performed for other sectors, too. Thus, long-term plans being made for appliers and administrators in decisive positions will be able to contribute to the economy of the country.

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