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STOCK RETURN FORECASTS WITH ARTIFICIAL NEURAL NETWORK MODELS

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Özet

İstanbul Menkul Kıymetler Borsası (İMKB) endekslerinin yapay sinir ağları modelleri ile tahmin edilebilirliği çeşitli çalışmalarda irdelenmiştir. Fakat söz konusu modellerle İMKB'de işlem gören hisse senetlerinin getirileri tahmin edilebilirliği üzerine bulgular bulunmamaktadır. Bu çalışmada yapay sinir ağları modellerinin, IMKB-30 endeksi içersinden seçilmiş hisse senetlerinin günlük getirilerini tahmin güçleri araştırılacaktır. Modellerin tahmin güçleri, işlem karlılık ölçütü doğrultusunda değerlendirilecektir. Çalışmanın sonuçları yapay sinir ağları modellerinin incelenen dönemlerin büyük çoğunluğunda al-ve-tut stratejisine üstünlük sağladıklarını göstermiştir.

Anahtar Kelimeler: *Yapay Sinir Ağları Modelleri, Hisse Senedi Getirilerinin Tahmin Edilmesi, Çok katmanlı Algılama Modelleri*

YAPAY SİNİR AĞLARI MODELLERİ İLE HİSSE SENEDİ GETİRİ TAHMİNLERİ

Abstract

Although several studies have examined the power of the artificial neural network models in predicting Istanbul Stock Exchange (ISE) indexes, there is no evidence on the predictive power of these models for ISE traded stock returns. This paper intends to examine the power of neural network models in prediction of daily returns of the selected stocks from ISE-30 index. The performance of the neural network models are evaluated by trading profits. The results of the study presented that the neural network models could beat the buy-and-hold strategy for most of the periods under investigation.

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1. Introduction

The neural network models have been utilized in several studies for stock market forecasting. Among these, some studies concentrated on index forecasting in one stock market[2], and other studies compared the forecast power of neural network models within international market indexes[3].

The predictability of the stock market indexes was studied by many researchers, as it was accepted that the market indexes were able to represent all stocks in the market. Moreover, index forecasting can avoid some firm specific unsystematic risk factors[4].

While vast majority of the literature was dedicated to index forecasting, a few studies concentrated on the predictability of the stock returns[5]. Although, the market index forecasting is more attractive, forecasting stock returns has some value for both the institutional and individual investors. From the institutional investors' point of view, the forecasted stock performances can provide some clues for their portfolio decision. On the other hand, the predictability of stock returns has a great importance especially for the individual investors, who are not capable of diversification.

This study aimed at examining the forecasting power of neural network models in predicting stock returns. Forecasting the stock returns of 5 commercial banks, which were included in ISE-30 index (Istanbul Stock Exchange 30) continuously during 2007-2008 period, were objective of this study. By the use of conjugate gradient algorithm, feedforward neural network models with different architectures were trained and the forecasting performance of model were analyzed according to financial performance measures.

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[2] See; E. Maasoumi – J. Racine, "Entropy and Predicability of Stock Market Returns", **Journal of Econometrics**, 107(1-2), 2002, s.291-312; A. Kanas, "Non-Linear Forecasts of Stock Returns", **Journal of Forecasting**, 22(4), 2003, s. 299-315; K.Y. Chen, "Evolutionary Support Vector Regression Modeling for Taiwan Stock Exchange Market Weighted Index Forecasting", **Journal of American Academy of Business**, 8(1), 2006, s. 241-247.

[3] See; A. Kanas – A. Yannopoulos, "Comparing Linear and Nonlinear Forecasts for Stock Returns", **Internationals Review of Economics and Finance**, 10(4), 2001, s. 383-398; M.T. Leung, *et.al.*, "Forecasting Stock Indices: A Comparison of Classification and Level Estimation Models", **International Journal of Forecasting**, 16(2), 2000, s.173-190; Y.F. Sun, *et.al*., "Optimal Partition Algorithm Of The RBF Neural Network And Its Application To Financial Time Series Forecasting", **Neural Computing & Applications**, 14, 2005, s. 36–44; D. Moreno - I. Olmeda "Is the Predictability of Emerging and Developed Stock Markets Really Exploitable?" **European Journal of Operational Research**, 182(1), 2007, s.436–454.

[4] S. Thawornwong - D. Enke, D., "Forecasting Stock Returns with Artificial Neural Networks", **Neural Networks in Business Forecasting**, Ed. Peter G. Zhang. Idea Group Inc., 2003, s.47-75.

[5] See; S.G. Eakins, - S.R. Stansell, "Can Value Based Stock Selection Yield Superior Risk-Adjusted Returns: An Application of Neural Networks", **International Review of Financial Analysis**, 12(1), 2003, s.83-97; D. Olson - C. Mossman, "Neural Network Forecasts of Canadian Stock Returns using Accounting Ratios", **International Journal of Forecasting**, 19(3), 2003, s.453-465.

This study is organized as follows. The next section will examine related studies on the stock market forecasting with neural network models in Istanbul Stock Exchange (ISE) and international stock markets. In the third section, the methodological considerations on forecasting stock returns with neural network models will be provided. The fourth section will present the empirical result. And hence, the fifth section concludes.

2. Literature Review

Although, the origins of neural network models dated back to McCulloch and Pitts's study in 1943[6], the first significant study on the application of the neural network models for stock market applications was White's study in 1988. This study was questioning the validity of the efficient market hypothesis by examining the forecasting accuracy of the neural network models on IBM stock's daily returns[7].

Following the White's study, many other studies were conducted in order to examine the forecasting effectiveness of the neural network models in international stock markets. While some studies were concentrated on measuring forecasting performance of neural network models based on several statistical and financial performance measures[8], there were some other studies, which compared the forecasting performances of neural network models with other statistical forecasting methods[9].

The literature, which compared the forecasting performances of the neural network models and benchmark models, presented mixed evidence on the superiority of one model over the others. The superiority of neural network models over other models in terms of different performance measures was reported in some studies[10]. However, some other studies argued that the forecast performance of neural network models were subject to change over time[11], and the neural network models were superior to regression only in highly volatile market conditions[12], and superiority of the neural network models over other models was not

[6] G.D. Garson, **Neural Networks: An Introduction Guide to Social Scientists**, London, SAGE Publications, 1998, s.1.
[7] H. White, "Economic Prediction Using Neural Networks: The Case of UBM Daily Stock Returns", **Proceedings of the IEEE International Conference on Neural Networks**, 1988, s.451-458.
[8] See; Ramazan Gencay, "Optimisation of Technical Trading Strategies and the Profitability in the Stock Markets" **Economic Letters**, 59(2), 1998, s.249-254;M. Lam, "Neural Network Techniques for Financial Performance Prediction: Integrating Fundamental and Technical Analysis" **Decision Support Systems**, 37(4), 2004, s.567– 581; S.H. Kim – S.H. Chun, "Graded Forecasting Using Array of Bipolar Predictions: Application of Probabilistic Neural Networks to a Stock Market Index" **International Journal of Forecasting**, 14(3), 1998, s.323-337.
[9] See; G.C. Lim, – P.D. McNelis, "The Effect of the Nikkei and the S&P on the All-Ordinaries: A Comparison of Three Models", **International Journal of Finance and Economics**, 3(3), 1998, s.217-228; J.V. Rodriguez, *et.al.*, "STAR and ANN Models: Forecasting Performance on Spanish Ibex-35 Stock Index", **Journal of Empirical Finance**, 12(3), 2005, s.490-509.
[10] See; Ramazan Gencay, "Non-Linear Prediction of Security Returns with Moving Average Rules", **Journal of Forecasting**, 15(3), 1996, s.165-174; Ramazan Gencay – T. Stengos, "Moving Average Rules, Volume and the Predicability of Stock Returns with Feedfoward Networks", **Journal of Forecasting**, 17(5-6), 1998, s.401-414.
[11] M. Qi, "Nonlinear Predicability of Stock Returns Using Financial and Economic Variables", **Journal of Business and Economics Statistics**, 17(4), 1999, s.419-429.
[12] V.S. Desai - R. Bharati, "”A Comparison of Linear regression and Neural Network Methods for Predicting Excess Returns on Large Stocks", **Annals of Operations Research**, 78, 1998a, s.127-163

significant[13] . Moreover, Desai and Bharati documented that GARCH was conditionally efficient than neural network models[14]. Kanas reported that Markov regime switching models and NN presented similar results in terms of forecast accuracy but Markov regime switching model was better in terms of forecast encompassing tests[15].

The applications of neural network models for Istanbul Stock Exchange (ISE) concentrated on the predictability of the ISE indexes, especially ISE-100 index. By the use of technical analysis indicators (momentum, MACD etc.), Diler (2003) studied on predicting the direction of the Istanbul Stock Exchange (ISE) for the following day. The results of the study presented that the direction of the IMKB-100 index could be predicted at a rate of 60.81%. [16]

In comparing the forecasting power of generalized feedforward (GNN) and multi layer perceptron models (BPNN) with the performance of moving averages rule, Egeli, *et al*. forecasted the ISE-100 index daily value. The generalized feedforward neural network model was found to be more appropriate for predicting stock market index value[17].

Furthermore, Avcı investigated the forecasting performance of the backpropagation neural network model for ISE-100 index with daily and sessional data. The findings of the study presented that increasing the data frequency (from daily to sessional data)[18], increase the forecast performance of neural network models.

Besides the studies, which examined only the neural network models' forecasting performance, there were some other studies that compared forecasting performances of the neural network models with other statistical forecasting techniques. All of these studies utilized the linear regression model as a benchmark model. Among this type of studies, Altay and Satman compared the forecast performances of neural network models with the linear regression for ISE-30 and ISE-All indexes. The forecasting performance of the backpropagation neural network model with different architectures investigated for daily, weekly and monthly data. The findings of the study showed that the forecasting performance of neural network models on the basis of statistical performance measures for daily and monthly data were failed to outperform the liner regression model, however the neural network models were able to predict the direction of the indexes more accurately.

[13] See; V. Dropsy, "Do Macroeconomic Factors Help in Predicting International Equity Risk Primia?: Testing the Out-of-Sample Accuracy of Linear and Nonlinear Forecasts" **Journal of Applied Business Research**, 12(3), 1996, s.120-127; Moreno - Olmeda, 2007; 1998; Rodriquez, et.al., 2005.
[14] V.S. Desai, - R. Bharati, "The Efficiency of Neural Networks in Predicting Returns on Stock and Bond Indices", **Decision Sciences**, 29(2), 1998b
[15] Kanas, 2003, s. 299-315.
[16] Ali İhsan Diler, "İMKB Ulusal-100 Endeksinin Yönünün Yapay Sinir Ağları Hata Geriye Yayma Yöntemi ile Tahmin Edilmesi", **İMKB Dergisi**, 25-26, 2003, s.65-81.
[17] Birgul Egeli, et.al., "Stock Market Prediction Using Artificial Neural Networks", **Proceedings of the 3rd Hawaii International Conference on Business**, Hawai, 2003.
[18] Emin Avcı, "Forecasting Daily and Sessional Returns of the ISE-100 Index with Neural Network Models", **Doğus Üniversitesi Dergisi,** 8(2), 2007, s. 128-142.

Moreover, when the returns calculated from a hypothetical portfolio, neural network models were able to beat the linear regression and buy-and-hold strategy[19].

In the same manner, Karaatlı *et al*. compared the monthly forecast performance of backpropagation neural network model and linear regression for ISE-100 index. On the basis of root mean square error (RMSE), it was found that the neural network model dominate the linear regression[20].

In comparing forecasting performances of the neural network model and stepwise regression, Çinko and Avcı utilized the ISE-100 index daily and sessional data. For both of the sessional and daily analysis, neural network model was superior to regression for all the periods based on the normalized mean square error and trend accuracy. However, according to mean square error performance measure, the stepwise regression dominated the neural network model for some periods under investigation[21].

4. Predictability of Stock Returns with Neural Network Models

As the applications of neural network models for stock market forecasting was concentrated on the ISE indexes, there was no evidence on the predictability of stock returns by the use of neural network models for the stocks traded in ISE. In order to contribute the literature, this study examined the forecast performance of neural network models for predicting stock returns.

Total of 5 commercial banks, stock of which were continuously included in ISE-30 index during 2007-2008, were selected for the purpose of this study. These banks were Akbank, Garanti Bank, Sekerbank, Vakıf Bank and Yapı Kredi Bank. By the use of 1 May 2007 – 30 September 2008 daily data, it was intended to forecast the return of these stocks during 5 months period continuously. These periods are determined as May 2008, June 2008, July 2008, August 2008 and hence September 2008. The methodological details are presented in the following pages.

4.1. Data

The data sets were including daily closing prices, daily weighted average prices and trading volumes information for selected stocks between 1 May 2007 and 30 September 2008. In order to reach a stationary data at some level, original data was transformed with logarithm operator. The natural logarithm or the logarithmic difference is the most common technique in literature in transforming the raw data set[22]. The

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[19] Erdinc Altay - M. Hakan Satman, "Stock Market Forecasting: Artificial Neural Networks and Linear Regression Comparison in an Emerging Market", **Journal of Financial Management and Analysis**, 18(2), 2005, s.18-33.

[20] Meltem Karaatlı, *et.al.*, "Hisse Senedi Fiyat Hareketlerinin Yapay Sinir Ağları Yöntemi ile Tahmin Edilmesi", **Balıkesir Üniversitesi İİBF Dergisi**, 2(1), 2005, s.22-48.

[21] Murat Çinko - Emin Avcı, "A Comparision Of Neural Network and Linear Regression Forecasts Of The ISE-100 Index". **Marmara Üniversitesi Sosyal Bilimler Enstitüsü Öneri Dergisi**, 7(28), 2007, s. 301-307.

[22] See; A.F. Darrat, - M. Zhong, "On testing the Random -Walk Hypothesis: Model Comparison Approach", **The Financial Review**, 35(3), 2000, s.105-124; F.F. Rodriguez, *et.al.*, "On the Profitability of Technical Trading Rules Based on Artificial Neural Networks: Evidence from Madrid Stock Market", **Economic Letters**, 69(1), 2000, s.89-94.

transformation of the price series was applied because such transformation could remove the long-term trend and log compression reduces the effect of outliers (often a result of exogenous shocks). Moreover, transformation could reduce volatility of the data set.

The transformation of the price data was achieved by:

$$r_t = \ln\left({y_t}/{y_{t-1}} \right) \qquad (1)$$

where, r_t was denoting the return at time t, and y_t, y_{t-1} were the stock prices for time t and $t-1$ respectively.

Table 1. List of Input Variables

1.	Lagged change in weighted average price for 1 day
2.	Lagged change in weighted average price for 3 days
3.	Lagged change in weighted average price for 5 days
4.	Lagged change in volume for 1 day.
5.	Lagged change in volume for 3 days.
6.	Lagged change in volume for 5 day.
7.	Moving average for change in weighted average price for 3 days
8.	Moving average for change in weighted average price for 5 days
9.	Moving average for in volume for 3 days
10.	Moving average for in volume for 5 days

Lagged change in weighted average price, change in trading volume, the moving averages of price series and volume constituted the input variables to the model. These variables were determined in accordance with the applications in literature. The list of input variables provided in *Table 1*.

Although, the importance of economic variables on ISE was found in various studies[23], such variables were not included in the study, as the usefulness of the economic variables in neural network modelling was not clear. While, O'Connor and Madden stated that economic variables (exchange rates and crude oil prices) in addition to financial variables increase the forecast performance in term of profitability and directional forecast[24]; Lam argued that macroeconomic variables did not provide statistically significant improvements in forecast performance[25]. Moreover, Stansell and Eakins depicted the usefulness of economic variables however, stressed on importance of selecting

[23] See; Hurşit Gunes, - Burak Saltoglu, İMKB Getiri Volatilitesinin Makroekonomik Konjonktür Bağlamında İrdelenmesi, İstanbul Menkul Kıymetler Borsası Yayınları; 1998; M. Ozcam, **An Analysis Of The Macroeconomic Factors That Determine The Stock Returns**, Sermaye Piyasası Kurulu Yayınları, No.75, 1997.

[24] N. O'Connor – G. Madden, "A Neural Network Approach to Predicting Stock Exchange Movements Using External Factors", **Knowledge-Based Systems**, 19(5), 2006, s.376.

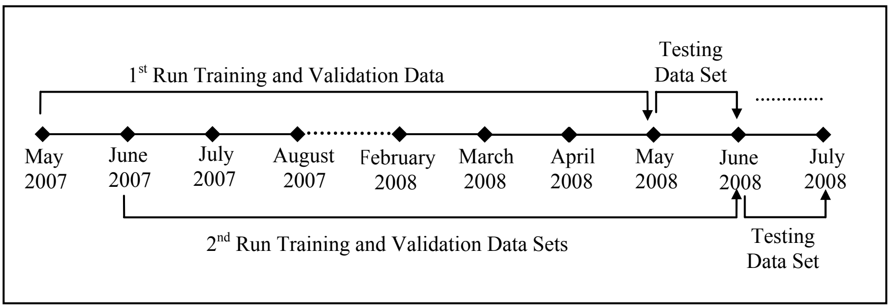
[25] Lam, 2004, s. 577.

appropriate economic data[26]. On the other hand, economic data was mostly available for monthly or quarterly basis, and as a matter of fact it was not suitable for daily analysis.

In order to investigate the performance of neural network model in different investment periods data sets for each stock were divided into five subsets. Each subset was organised to cover 1 year data. 1 year period was selected as more current training data was best for optimal forecasting performance[27]. Furthermore, in order to train, validate and test the model, each subset was divided into three. Following the literature[28], approximately 70%, 20% and 10% of each subset were utilised as training data set, validation data set and test data set respectively.

The moving window approach was adopted in the organization of the data set. In another saying, when a new data was received, the oldest data from the training data set was dropped and new data was added to the data set. The advantage of the moving window approach was its ability to capture the environmental changes as it utilized more recent data. Moreover, by utilizing such approach, the forecasting performance of neural network models would be observed on a continuous manner.

Figure 1. Moving Window Approach



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[26] S.R. Stansell – S.G. Eakins, "Forecasting the Direction of Change In Sector Stock Indexes: An Application of Neural Networks", **Journal of Asset Management**, 5(1), 2003, s.37-48.
[27] S. Walczak, "An Empirical Analysis of Data Requirements for Financial Forecasting with Neural Networks", **Journal of Management Information Systems**, 17(4), 2001, s.219.
[28] See; G.J. Deboeck, G.J. – M. Cader, "Pre- and Postprocessing of Financial Data", **Trading on the Edge**, Ed. Guido J. Deboeck, New York, John Wiley & Sons Inc., 1994, s. 27-45; I. Kaastra,– M. Boyd, "Designing a Neural Network for Forecasting Financial and Economic Time Series", **Neurocomputing**, 10(3), 1996, s. 215-236; Yao, J.T. and Tan, C.L., "Guidelines for Financial Forecasting with Neural Networks", **Proceedings of International Conference on Neural Information Processing**, Shanghai, 14-18 November 2001.

Figure 1 illustrated the moving window approach utilized in this study. For example, in the first run to forecast the daily stock returns for May 2008, the data from May 2007 to end of April 2008 would be considered as training (70% of whole subset approximately) and validation (20% of whole subset approximately) data sets. And, the model would be tested during the trading days of May 2008. In order to forecast the daily returns for June 2008 in the second run, the May 2007 data would be dropped from the training and validation data set, but June 2008 data would be included. Although, such data organization would provide continuous forecasts of stock returns, as a result of changing number of trading days in the market, the sizes of training, validation and test data sets would not be equal for each subset. However, such mismatches in the sample periods would not distort overall results of the analysis.

4.2. Methodology

Although, there several neural network models were introduced to the literature, this study utilized three-layer (one hidden layer) multilayer perceptron model with backpropagation algorithm, as these models mathematically proved to be universal approximator for any continuous function[29]. Moreover, multilayer perceptron model became a standard forecasting tool in neural network literature as over 80% of the studies utilized this model[30].

There were some evidences on the superiority of two hidden layer models over one hidden layer[31], however, marginal utility and cost of developing complex architecture should be taken into account and less complicated model would be the best[32]. Moreover, in examining predictability of ISE-100 index, Egeli, et.al. reported that 1 hidden layer neural network model was better than 2, 3 and 4 hidden layer models in terms of forecasting accuracy[33].

Three different multilayer perceptron models were trained with different architectures. The first model had 5 processing elements (will be denoted as PE-5 model) in the hidden layer, the second one had 10 processing elements in the hidden layer (will be denoted as PE-10 model), and the third one had 12 processing elements in the hidden layer (will be denoted as PE-12 model). The number of hidden nodes was determined by

[29] K. Hornik, *et.al.*, “Multilayer Feedforeward Networks Are Universal Approximators. **Neural Networks**, 2(5), 1989, s. 359-366; G. Cybenko, “Approximation by Superpositions of a Sigmoidal Function”, **Mathematics of Control. Signal and Systems**, 2, 1989, s.303-314; K. Hornik, *et.al.*, “Universal Approximation of an Unknown Mappings and its Derivatives Using Multilayer Feedforward Neural Networks”, **Neural Networks**, 3(5), 1990, s. 551-560.

[30] M. Adya – F. Collopy, “How effective are neural networks at forecasting and prediction? A review and evaluation”, **Journal of Forecasting**, 17, 1998, s. 487-495.

[31] See; J. Yao, *et.al.*, “Neural Networks for Technical Analysis: A Study on KLCI”, **International Journal of Theoretical and Applied Finance**, 2(2), 1999, s.221-241; K. Schierholt, - C.H. Dagli, “Stock Market Prediction Using Different Neural Network Classification Architectures”, **Proceedings of IEEE/IAFE Conference on Computational Intelligence for Financial Engineering**, New York, 24-26 March 1996.

[32] Lam, 2004, s.577.

[33] Egeli, et.al., 2003.

following the heuristics advices[34]. Application of more than one heuristic advice was identical to a trial and error and time consuming, it was unfortunately unavoidable[35].

Figure 2. Multilayer Perceptron Model

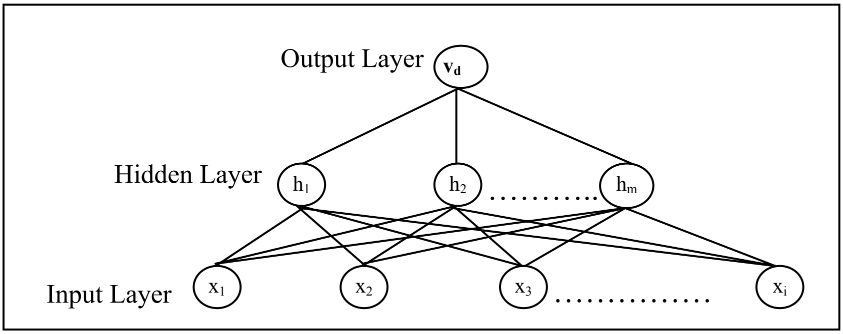

Figure 2 presented a simple multilayer perceptron model. The input layer composed of M units of x_i (i = 1,2….N), the hidden layer composed of Z processing entities of h_m (m = 1,2,…..Z), and hence one output layer was denoted by v_d. The output for the model could be presented as:

$$\hat{y} = g\left[\sum_{m=0}^{Z} w_{md}\, g\left(\sum_{i=0}^{M} w_{im} x_i\right)\right]^f \quad (2)$$

(3)

where, w_{im} represented the weights between input and hidden processing units, w_{md} was the weights between hidden processing and the output unit, hence $g(.)$ and $g(.)^f$ were the transformation functions for hidden processing elements and output unit respectively.

The transformation functions for hidden and output layers were hyperbolic tangent, $g(.)$, and linear functions, $g(.)^f$, respectively. The transformation functions are presented mathematically in *Equation 3*:

[34] R. Callan, **The Essence of Neural Networks**, Essex, Prentice Hall, 1999; G. Zhang, *et.al.*, “Forecasting with Artificial Neural Networks: The State of the Art”, **International Journal of Forecasting**, 14(1), 1998, s. 35-62.

[35] L. Ma – K. Khorasani, “New Training Strategies for Constructive Neural Networks with Application to Regression Problems”, **Neural Networks**, 17(4), 2004, s.589.

$$g(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

$$g(x)^{f} = x \tag{3}$$

Several first order and second order mathematical optimization methods were utilized in the literature. In this study one of the second order optimization methods, the scaled conjugate gradient algorithm, was utilized. The advantage of the scaled conjugate gradient was its ability to avoid the line search procedure, which was for other conjugate methods.

4.3. Performance Measures

In order to evaluate the forecast performance of neural network models alternative performance measures could be utilized. The performance measures used in literature for neural network models can be investigated under 2 groups: statistical methods and profitability.

Statistical methods basically measure the forecasting accuracy of the neural network models beyond the training data. In these statistical methods the forecasting errors are calculated as the difference between the actual value and the forecasted value. Although there are many different statistical methods existing in literature, most common methods mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE).

By the use of statistical performance measures the statistical correctness of the models under examination could be determined, however the basic objective of the forecasting efforts was to beat the market, or in other words, gaining more returns than the average market return. Although, the statistical methods techniques gave a clue about the correctness of the neural network models, those methods could not guarantee the profitability of the trading strategies developed in accordance with the neural network models.

In this study the profitability of the neural network models was analyzed by the use of simple trading strategy. The trading strategy was:

$$\text{Trading Strategy} = \begin{cases} If,\ y_t \quad > 0; \text{Buy, otherwise no position} \\ If,\ y_{t+1} > 0; \text{Hold position, otherwise sell} \end{cases} \tag{4}$$

where, y_t was representing the forecasted stock return for trading period t. The trading costs and taxes were neglected.

The profitability of the trading strategy, which was guided by neural network models, was compared to buy-and-hold return for each stock. Moreover, an equally weighted portfolio will be constructed and managed by trading strategy. The performances such portfolio also be compared to buy and hold return of equally weighted portfolio of these stocks for each investment period.

5. Empirical Findings

By the use input variables, which were stated in Table 1, the daily stock returns for the selected commercial banks were forecasted by neural network models. The forecasts of neural network models were utilized by a simple trading strategy. And, hence the resulting monthly returns of the selected stocks were calculated. Table 2 presents the returns from the selected stocks generated by the neural network model guided trading strategies and buy-and-hold returns[36].

The monthly buy-and-hold returns for stocks were negative for all of the months except July and June for Sekerbank. When the returns generated by neural network models were analyzed, the neural network models were able to limit those losses. For example, while the buy-and-hold returns for Akbank in May was -19% (approx.), the loss on PE-5 model guided strategy was -0,71%. There were also some other cases where the neural network models could generate positive returns. For example, in August, while the buy-and-hold return for Akbank was -6% (approx.), the return from PE-10 model guided strategy was 11,6%.

As a general view, within 25 samples (5 banks and 5 months), at least one of the neural network models could beat the buy-and-hold strategy in each stock for each month with 3 exceptions. These exceptions were the June of Sekerbank; July of Sekerbank and Vakifbank. All exceptions were the months with positive buy-and-hold return.

On the other hand, only in 11 observations (out of 25), both neural network models were superior to buy-and-hold strategy in the same month.

[36] The statistical performances of the neural network models were presented in the appendix.

Table 2 Returns from Trading Strategy and Buy-and-Hold Strategy

		PE-5	PE-10	PE-12	Buy & Hold
Akbank	May	-0,0071	-0,1122	-0,1563	-0,1928
	June	0,0000	-0,0192	-0,1582	-0,1141
	July	0,3513	0,3264	0,4890	0,4890
	August	-0,0702	0,1160	0,0119	-0,0606
	September	0,0964	-0,1282	-0,0573	-0,0532
Garanti Bank	May	-0,1172	-0,1312	-0,1110	-0,1957
	June	-0,1899	-0,0292	-0,0919	-0,5247
	July	0,1238	0,2845	0,2664	0,2405
	August	0,0052	-0,0587	0,0000	-0,0946
	September	-0,1302	-0,1319	-0,0277	-0,1003
Şekerbank	May	-0,2062	-0,0243	0,0398	-0,2834
	June	0,0044	0,0000	0,0044	0,0422
	July	0,0250	-0,0280	0,0184	0,0383
	August	-0,0152	0,0152	-0,0179	-0,0978
	September	0,0000	-0,0696	-0,1286	-0,1791
Vakıf Bank	May	0,0156	0,0401	-0,1652	-0,1921
	June	-0,0493	-0,0030	-0,0666	-0,2516
	July	0,1524	0,1870	0,3168	0,4378
	August	-0,0491	-0,0758	0,0163	-0,0502
	September	-0,2354	0,0241	-0,2218	-0,0535
Yapı Kredi Bank	May	0,0783	0,0605	0,0051	0,0188
	June	-0,1195	-0,1416	-0,0639	-0,2390
	July	0,0958	0,1754	0,2055	0,1609
	August	0,0455	0,0128	0,0224	-0,0036
	September	0,0727	0,0061	-0,0042	0,0112

When the performances of neural network models were compared with the buy-and-hold strategy, the PE-5, PE-10 and PE-12 models could dominate in 16, 17 and 17 months respectively. However, no models could continuously dominate the buy-and-hold strategy and other strategies. The PE-5, PE-10 and PE-12 models were superior to other models in 8, 7 and 7 months respectively. As, stated above the buy-and-hold strategy dominated the neural network models in 3 months.

The equally weighted portfolio performance of the neural network models and buy-and-hold strategy are presented in Table 3. According to monthly returns, the portfolios managed by neural network models were superior to buy and hold return of the equally weighted portfolio for each month except for July. July was the only month that had a positive return within the investigated periods. Buy-and-hold return for the equally weighted portfolio for July was 27%, which was a tremendous return in the financial markets. The nearest performance was achieved by PE-12 model by 25% approximately.

Table 3 Portfolio Performances

	PE-5	**PE-10**	**PE-12**	**Buy & Hold**
May	-0,0473	-0,0334	-0,0775	-0,1691
June	-0,0709	-0,0386	-0,0752	-0,2174
July	0,1496	0,1890	0,2592	0,2733
August	-0,0168	0,0019	0,0066	-0,0614
September	-0,0393	-0,0599	-0,0879	-0,0750
Cumulative	**-0,0246**	**0,0590**	**0,0251**	**-0,2495**

For the remaining months (May, June, August and September), the equally weighted portfolio with buy-and-hold strategy realized negative returns. Although, the portfolios guided by neural network models could not generate positive returns for all months, the losses for these portfolios were much less than the buy-and-hold strategy. Furthermore, for August, the PE-10 and PE-12 models guided portfolios could generate positive returns.

The contribution of the neural network models was more clear when the cumulative returns were investigated. After 5 recursive investment periods, buy-and-hold strategy ended up with return of -24,95%. While the neural network models generated -2,46%, 5,90% and 2,51%.

6. Conclusion

This study investigated the effectiveness of neural network models in stock return forecasting. For this purpose, 5 stocks, which were continuously listed in ISE-30 index were selected. By the use of three different neural network models, daily returns were forecasted on daily basis for 5 recursive months. The results were compared with the buy-and-hold strategy.

The findings of the study presented that the neural network models were able to dominate the buy-and-hold strategy for most of the periods under investigation. In line with findings of other researches about stock index forecasting, the neural network models were also effective in stock return forecasting for the selected stocks.

Although, the findings of this study support the effectiveness of neural network models in stock market forecasting, these finding cannot be generalized. In order to generalize these findings, some other researches should be handled with other stocks listed in the ISE. The results may be subject to change especially for neglected stocks.

Appendix : Statistical Performance Measures

		PE-5					PE-10					PE-12				
		May	June	July	August	September	May	June	July	August	September	May	June	July	August	September
Akbank	MSE	0,0007	0,0014	0,0027	0,0012	0,0045	0,0008	0,0014	0,0041	0,0010	0,0046	0,0008	0,0012	0,0026	0,0011	0,0050
	NMSE	1,1774	1,6369	1,1582	1,2111	1,0051	1,3662	1,5949	1,7226	1,0191	1,0328	1,3031	1,3873	1,0975	1,1034	1,1279
	MAE	0,0217	0,0298	0,0413	0,0249	0,0508	0,0240	0,0293	0,0517	0,0270	0,0509	0,0225	0,0253	0,0366	0,0251	0,0536
	r	0,3443	0,1067	0,1683	-0,1615	0,1180	0,2105	0,0252	-0,2244	0,6546	-0,1654	0,2147	-0,2112	0,1133	0,0300	-0,1805
Garanti Bank	MSE	0,0013	0,0177	0,0024	0,0006	0,0034	0,0013	0,0167	0,0032	0,0006	0,0033	0,0012	0,0168	0,0033	0,0004	0,0033
	NMSE	1,2252	1,1637	1,1435	1,5877	1,0605	1,2257	1,0941	1,5059	1,4521	1,0247	1,1609	1,1027	1,5280	0,9014	1,0255
	MAE	0,0303	0,0713	0,0424	0,0191	0,0483	0,0310	0,0545	0,0492	0,0163	0,0458	0,0290	0,0674	0,0475	0,0164	0,0464
	r	-0,0111	-0,0566	0,0377	-0,0245	-0,1790	0,0624	0,1469	0,2776	0,0506	0,0605	0,3187	0,0539	-0,0976	0,3803	0,0342
Şeker Bank	MSE	0,0028	0,0010	0,0013	0,0011	0,0046	0,0027	0,0009	0,0016	0,0008	0,0039	0,0027	0,0009	0,0013	0,0009	0,0039
	NMSE	1,1848	1,2786	1,2177	1,2961	1,2737	1,1277	1,2090	1,4533	0,9637	1,0861	1,1216	1,2583	1,2518	1,0683	1,0884
	MAE	0,0373	0,0247	0,0263	0,0252	0,0570	0,0364	0,0241	0,0305	0,0226	0,0540	0,0368	0,0246	0,0290	0,0234	0,0539
	r	0,2694	0,0182	-0,1574	-0,2083	-0,3881	0,2258	0,0624	0,0591	0,3009	-0,1934	0,0264	0,0146	-0,1754	-0,1807	-0,2131
Vakıflar Bank	MSE	0,0009	0,0011	0,0038	0,0013	0,0078	0,0008	0,0011	0,0036	0,0008	0,0058	0,0020	0,0012	0,0036	0,0014	0,0069
	NMSE	1,1828	1,0695	1,1813	2,4548	1,2800	1,0069	1,0804	1,1371	1,4341	0,9404	2,5136	1,1839	1,1171	2,6814	1,1218
	MAE	0,0206	0,0241	0,0456	0,0245	0,0732	0,0188	0,0215	0,0434	0,0204	0,0596	0,0352	0,0236	0,0416	0,0305	0,0685
	r	-0,1193	0,2972	0,0234	0,0637	-0,5061	0,3894	0,2402	0,1555	-0,2859	0,3292	-0,3435	0,1013	0,2170	0,3076	-0,4148
Yapı Kredi Bank	MSE	0,0013	0,0011	0,0024	0,0005	0,0026	0,0013	0,0009	0,0021	0,0006	0,0029	0,0013	0,0008	0,0021	0,0005	0,0028
	NMSE	1,0037	1,6451	1,1634	1,0060	0,9606	1,0172	1,4451	1,0132	1,0929	1,0490	0,9917	1,1872	1,0034	1,0443	1,0074
	MAE	0,0298	0,0248	0,0394	0,0200	0,0437	0,0285	0,0216	0,0327	0,0192	0,0451	0,0276	0,0202	0,0341	0,0191	0,0455
	r	0,1750	-0,0946	0,0959	0,3617	0,2235	0,1261	-0,1035	0,0039	-0,0887	0,0048	0,2166	0,1411	0,2515	0,3717	0,1711

References

ADYA, M. and F. COLLOPY, “How effective are neural networks at forecasting and prediction? A review and evaluation”, **Journal of Forecasting**, 17, 1998, s. 487-495.

ALTAY, Erdinç and M. Hakan SATMAN, “Stock Market Forecasting: Artificial Neural Networks and Linear Regression Comparison in an Emerging Market”, **Journal of Financial Management and Analysis**, 18(2), 2005, s.18-33.

AVCI, Emin, “Forecasting Daily and Sessional Returns of the ISE-100 Index with Neural Network Models”, **Doğus Üniversitesi Dergisi,** 8(2), 2007, s. 128-142.

CALLAN, R., **The Essence of Neural Networks**, Essex, Prentice Hall, 1999.

CHEN, K.Y., “Evolutionary Support Vector Regression Modeling for Taiwan Stock Exchange Market Weighted Index Forecasting”, **Journal of American Academy of Business**, 8(1), 2006, s. 241-247.

ÇİNKO, Murat and Emin AVCI, “A Comparision Of Neural Network and Linear Regression Forecasts Of The ISE-100 Index”. **Marmara Üniversitesi Sosyal Bilimler Enstitüsü Öneri Dergisi**, 7(28), 2007, s. 301-307.

CYBENKO, G., “Approximation by Superpositions of a Sigmoidal Function”, **Mathematics of Control. Signal and Systems**, 2, 1990, s. 303-314.

DARRAT, A.F. and M. ZHONG, “On testing the Random -Walk Hypothesis: Model Comparison Approach”, **The Financial Review**, 35(3), 2000, s.105-124.

DEBOECK, G.J. and M. CADER, “Pre- and Postprocessing of Financial Data”, **Trading on the Edge**, Ed. Guido J. Deboeck, New York, John Wiley & Sons Inc., 1994, s. 27-45.

DESAI, V.S. and R. BHARATI, ”A Comparison of Linear regression and Neural Network Methods for Predicting Excess Returns on Large Stocks”, **Annals of Operations Research**, 78, 1998a, s.127-163.

DESAI, V.S. and R. BHARATI, “The Efficiency of Neural Networks in Predicting Returns on Stock and Bond Indices”, **Decision Sciences**, 29(2), 1998b, s.405-425.

DİLER, Ali İhsan, “İMKB Ulusal-100 Endeksinin Yönünün Yapay Sinir Ağları Hata Geriye Yayma Yöntemi ile Tahmin Edilmesi”, **İMKB Dergisi**, 25-26, 2003, s.65-81.

DROPSY, V., “Do Macroeconomic Factors Help in Predicting International Equity Risk Primia?: Testing the Out-of-Sample Accuracy of Linear and Nonlinear Forecasts” **Journal of Applied Business Research**, 12(3), 1996, s.120-127.

EAKINS, S.G. and S.R. STANSELL, “Can Value Based Stock Selection Yield Superior Risk-Adjusted Returns: An Application of Neural Networks”, **International Review of Financial Analysis**, 12(1), 2003, s.83-97.

EGELİ, Birgul, et.al., “Stock Market Prediction Using Artificial Neural Networks”, **Proceedings of the 3rd Hawaii International Conference on Business**, Hawai, 2003.

GARSON, G.D., **Neural Networks: An Introduction Guide to Social Scientists**, London, SAGE Publications, 1998.

GENCAY, Ramazan and T. STENGOS, “Moving Average Rules, Volume and the Predicability of Stock Returns with Feedfoward Networks”, **Journal of Forecasting**, 17(5-6), 1998, s.401-414.

GENCAY, Ramazan, “Non-Linear Prediction of Security Returns with Moving Average Rules”, **Journal of Forecasting**, 15(3), 1996, s.165-174.

GENCAY, Ramazan, “Optimisation of Technical Trading Strategies and the Profitability in the Stock Markets” **Economic Letters**, 59(2), 1998, s.249-254.

GUNES, Hurşit and Burak SALTOGLU, **İMKB Getiri Volatilitesinin Makroekonomik Konjonktür Bağlamında Irdelenmesi**, İstanbul Menkul Kıymetler Borsası Yayınları, 1998.

HORNIK, K., M. STINCHCOMBE, and H. WHITE, “Multilayer Feedforeward Networks Are Universal Approximators”, **Neural Networks**, 2(5), 1989, s. 359-366.

HORNIK, K., M. STINCHCOMBE, and H. WHITE, “Universal Approximation of an Unknown Mappings and its Derivatives Using Multilayer Feedforward Neural Networks”, **Neural Networks**, 3(5), 1990, s.551-560.

KAASTRA, I. and M. BOYD, “Designing a Neural Network for Forecasting Financial and Economic Time Series”, **Neurocomputing**, 10(3), 1996, s. 215-236.

KANAS, A. “Non-Linear Forecasts of Stock Returns”, **Journal of Forecasting**, 22(4), 2003, s. 299-315.

KANAS, A. and A. YANNOPOULOS, “Comparing Linear and Nonlinear Forecasts for Stock Returns”, **Internationals Review of Economics and Finance**, 10(4), 2001, s.383-398.

KARAATLI, Meltem, İ. GÜNGÖR, Y. DEMİR and Ş. KALAYCI, “Hisse Senedi Fiyat Hareketlerinin Yapay Sinir Ağları Yöntemi ile Tahmin Edilmesi”, **Balıkesir Üniversitesi İİBF Dergisi**, 2(1), 2005, s.22-48.

KIM, S.H.and S.H. CHUN, “Graded Forecasting Using Array of Bipolar Predictions: Application of Probabilistic Neural Networks to a Stock Market Index” **International Journal of Forecasting**, 14(3), 1998, s.323-337.

LAM, M., "Neural Network Techniques for Financial Performance Prediction: Integrating Fundamental and Technical Analysis" **Decision Support Systems**, 37(4), 2004, s.567–581.

LEUNG, M.T., H. DAOUK and A. CHEN, "Forecasting Stock Indices: A Comparison of Classification and Level Estimation Models", **International Journal of Forecasting**, 16(2), 2000, s.173-190.

LIM, G.C. and P.D. MCNELIS, "The Effect of the Nikkei and the S&P on the All-Ordinaries : A Comparison of Three Models", **International Journal of Finance and Economics**, 3(3), 1998, s.217-228.

MA, L. and K. KHORASANI, "New Training Strategies for Constructive Neural Networks with Application to Regression Problems", **Neural Networks**, 17(4), 2004, s.589-609.

MAASOUMI, E. and J. RACINE, "Entropy and Predicability of Stock Market Returns", **Journal of Econometrics**, 107(1-2), 2002, s.291-312.

MORENO, D. and I. OLMEDA "Is the Predictability of Emerging and Developed Stock Markets Really Exploitable?" **European Journal of Operational Research**, 182(1), 2007, s.436–454.

O'CONNOR, N. and G. MADDEN, "A Neural Network Approach to Predicting Stock Exchange Movements Using External Factors", **Knowledge-Based Systems**, 19(5), 2006, s. 371–378.

OLSON, D. and C. MOSSMAN, " Neural Network Forecasts of Canadian Stock Returns using Accounting Ratios", **International Journal of Forecasting**, 19(3), 2003, s.453-465.

OZCAM, M., **An Analysis Of The Macroeconomic Factors That Determine The Stock Returns**. Sermaye Piyasası Yayınları, No.75, 1997.

QI, M., "Nonlinear Predicability of Stock Returns Using Financial and Economic Variables", **Journal of Business and Economics Statistics**, 17(4), 1999, s.419-429.

RODRIGUEZ, F.F., C. MARTEL and S.S. RIVERO, "On the Profitability of Technical Trading Rules Based on Artificial Neural Networks: Evidence from Madrid Stock Market", **Economic Letters**, 69(1), 2000, s.89-94.

RODRIGUEZ, J.V, S. TORRA, and J.A. FELIX, "STAR and ANN Models: Forecasting Performance on Spanish Ibex-35 Stock Index", **Journal of Empirical Finance**, 12(3), 2005, s.490-509.

SCHIERHOLT, K., and C.H. DAGLI, "Stock Market Prediction Using Different Neural Network Classification Architectures", **Proceedings of IEEE/IAFE Conference on**

Computational Intelligence for Financial Engineering, New York, 24-26 March 1996.

STANSELL, S.R. and S.G. EAKINS, “Forecasting the Direction of Change In Sector Stock Indexes: An Application of Neural Networks”, **Journal of Asset Management**, 5(1), 2003, s.37-48.

SUN, Y.F., Y.C. LIANG, W.L. ZHANG, H.P. LEE, W.Z. LIN and L.J. CAO, “Optimal Partition Algorithm Of The RBF Neural Network And Its Application To Financial Time Series Forecasting”, **Neural Computing & Applications**, 14, 2005, s. 36–44.

THAWORNWONG, S. - D. Enke, D., “Forecasting Stock Returns with Artificial Neural Networks”, **Neural Networks in Business Forecasting**, Ed. Peter G. Zhang. Idea Group Inc., 2003, s.47-75.

WALCZAK, S. “An Empirical Analysis of Data Requirements for Financial Forecasting with Neural Networks”, **Journal of Management Information Systems**, 17(4), 2001, s. 203-222.

WHITE, H., “Economic Prediction Using Neural Networks: The Case of UBM Daily Stock Returns”, **Proceedings of the IEEE International Conference on Neural Networks**, 1988, s.451-458.

YAO, J., C.L TAN and H.L. POH, “Neural Networks for Technical Analysis: A Study on KLCI”, Inter**national Journal of Theoretical and Applied Finance**, 2(2), 1999, s.221-241.

YAO, J.T. and C.L. TAN, “Guidelines for Financial Forecasting with Neural Networks”, **Proceedings of International Conference on Neural Information Processing**, Shanghai, 14-18 November 2001.

ZHANG, G., *et.al.*, “Forecasting with Artificial Neural Networks: The State of the Art”, **International Journal of Forecasting**, 14(1), 1998, s. 35-62.