Financial Risk and Management Reviews
2015 Vol. 1, No. 2, pp. 53-67
ISSN(e): 2411-6408
ISSN(p): 2412-3404
DOI: 10.18488/journal.89/2015.1.2/89.2.53.67

STOCK MARKET INDEX PREDICTION WITH NEURAL NETWORK DURING FINANCIAL CRISES: A REVIEW ON BIST-100

Şakir SAKARYA[1] --- Mehmet YAVUZ[2†] --- Aslan Deniz KARAOĞLAN[3] --- Necati ÖZDEMİR[4]

[1]*Balikesir University, Department of Business Administration, Cağış Campus, Balıkesir, Turkey*

[2]*Necmettin Erbakan University, Fakulty of Science, Department of Mathematics-Computer Sciences, Meram, Konya, Turkey*

[3]*Balikesir University, Department of Industrial Engineering, Cağış Campus, Balıkesir, Turkey*

[4]*Balikesir University, Department of Mathematics, Cağış Campus, Balıkesir, Turkey*

ABSTRACT

Predetermining the future value of a variable is both quite important and rather difficult process in financial markets. In this context, especially in the last 15 years, Artificial Neural Networks (ANNs) are widely used in order to resolve various kinds of financial problems such as performing portfolio construction, stock index, and bankruptcy prediction. This study examines the predictability of daily and weekly returns of Borsa İstanbul (BIST)-100 Index during global crisis period (July 2007-December 2009) by using ANN. It differs from other similar studies in the literature as it: i) covers global crisis period, ii) predicts index value of the next day and next week and finally iii) uses seven different economic parameters (variables) as input. The results obtained suggest that ANN can be used quite successfully in this area and foresee correctly the value for next day and next week with an accuracy margin error of less than 5% even for unknown samples. The ANN model in this study is developed using MATLAB R2008b.

Keywords: Financial crises, Artificial neural networks, Index forecasting, BIST-100 index.

1. INTRODUCTION

In recent years, Artificial Neural Networks (ANNs) are widely used in the solution of financial problems. For instance to measure the performance of stocks, to determine exchange rates direction, to predict company bankruptcy, to forecast financial crisis, to detect manipulative operations, to estimate stocks and indices, and to optimize portfolio, etc.

There are two approaches that are widely used in prediction of stock market indices with ANN. The first one is an analysis of the relationship between stock prices, dividends, and trading volume and the other one is testing the relationship between the stock market index and other

† Corresponding author

macro-economic variables. As daily price movements in the financial markets are dynamic and fluctuating, computer-based learning algorithms, such as neural networks, are quite appropriate in predicting financial markets' direction (Oh *et al.*, 2006).

As there is not yet a method that determines exact stock prices, working on algorithms for the prediction of these stock prices is among the prior interest areas of financial communities. In addition, high uncertainty and volatility in the stock prices show that investing in these carries a great risk. Besides, high returns of stocks have attracted the attention of many researchers, investors, and other relevant people. Moreover, the influence of many macro-economic factors, such as political events, firm policies, general economic conditions, investor expectations, institutional investor preferences, other stock market operations, and the psychology of investors etc. has an impact of the stock market prices (Wang *et al.*, 2011).

Financial crises disturb the macro-economic equilibrium and affect capital markets adversely. The financial crises in Turkey also have left deep scars and have negatively affected the macro-economic factors. One of these macro-economic factors that are affected by the financial crisis is Istanbul Stock Exchange (ISE) (Gençtürk, 2009). It is remarkable that studies on stock index prediction are quite few in Turkey. The purpose of this study is to show BIST-100 index predictability with feed forward neural network during the global financial crisis.

2. LITERATURE REVIEW

Studies about stock index prediction with neural networks have been performed about for 25 years. Kimoto *et al.* (1990) study on TOPIX (Tokyo Stock Exchange Prices Indexes) was one of the first studies performed on stock index prediction. They developed a number of learning algorithms and prediction methods for the TOPIX prediction system. They compared the neural network (NN) and multiple regression analysis (MRA) and as the result of their study they observed that NN learned the data well enough to show a very high correlation coefficient (0.991) and MRA even a lower correlation coefficient (0.543). This shows NN is more effective than MRA. Yoon and George (1991) studied stock price forecasting and compared neural networks to multiple discriminant analysis (MDA). They obtained that the mean success rate during the testing phase for the four-layered network was 77.5% as compared with MDA technique 65%. This result shows that NN method significantly enhanced the MDA model's stock price predictive power Yoon *et al.* (1993) compared neural networks to discriminant analysis (DA) and they found that the accuracy of ANN is 91%, whereas the accuracy of DA is 74%.

Mallaris and Linda (1996) studied S&P 500 Index in order to present a neural network which accurately forecasts the volatility most often used by traders using Black-Scholes formula to calculate implied volatility. The overall proportion of correct direction predictions was 0.794. The correlation between the neural network forecast and the future implied volatility was 0.8535 with a significance level of 0.0001. Mizuno *et al.* (1998) predicted buying and selling signals of Tokyo

Stock Exchange Prices Index (TOPIX) with an accuracy of 63% using the neural network system that they had developed. Phua *et al.* (2000) used the neural networks and genetic algorithm (GA) in order to estimate the Singapore Exchange (SGX) and examined 360 data between August 1998 and January 2000. They also considered the trading volume, opening price, closing price, the highest price and the lowest price of SGX and thus predicted SGX trend with an accuracy of 81%.

O'connor and Michael (2005) evaluated the effectiveness of using external indicators, such as commodity prices and currency exchange rates, in predicting Dow Jones Industrial Average (DJIA) index movements. Basing trading decisions on a neural network trained on a range of external indicators resulted with a yearly 23.5% profit while the DJIA index grew by 13.03% per annum. Li and Liu (2009) study on Shanghai Stock Exchange (SSE) proved that the Back Propagation (BP) network based on Levenberg-Marquardt (LM) algorithm can provide effective short term predictions after providing the network with the necessary training.

Guresen *et al.* (2011) evaluated the effectiveness of NN models known to be dynamic and effective NASDAQ Stock Exchange Index predicators. The models analyzed are MLP, dynamic artificial neural network (DAN2) and the hybrid neural networks using generalized autoregressive conditional heteroscedasticity (GARCH) to extract new input variables. They concluded that MLP is a powerful and practical tool for forecasting stock movements due to its small error rate (0.54%). Aghababaeyan *et al.* (2011) used the neural network standard feed-forward back propagation (FFB) in order to predict the Tehran Stock Exchange (TSE). They found that their prediction model can notify the direction of stock price movements with an accuracy of 83% when upcoming news is released. Wang *et al.* (2011) proposed a new approach to forecast Shanghai Composite Index (SCI) stock prices via the Wavelet De-noising-based Back Propagation (WDBP) neural network. To show the advantage of this new approach for stock index forecast, the WDBP neural network was compared with the single Back Propagation (BP) neural network using real data set and concluded that their WDBP model was more effective. Desai *et al.* (2012) presented a computational approach for predicting the S&P CNX Nifty 50 Index. For this approach they used a neural network based model in predicting the direction of the movement of the closing value for the next day with an accuracy of 82%. In Turkey, ANNs are used primarily in predicting the financial failure (Yıldız, 2001). Diler (2003) predicted BIST-100 Index trend for the next day up to 60.81% using ANN with error back propagation (BP) method.

In a similar study, Yildiz *et al.* (2008) estimated the trend of BIST-100 Index for the next day with a 74.91% accuracy using a NN model. Vural Barış (2007) estimated the daily closing prices of BIST Index with 3% error in his prediction study by developing an ANN model.

Akel and Bayramoğlu (2008), using a multi-layer perceptron (MLP) network, demonstrated that BIST Index prediction after and before period was possible during 2001 February crisis. Their model also generated a 73.68% signal about Index decrease and increase.

Kutlu and Bertan (2009) developed a feed forward neural network to predict daily BIST-100 Index direction. They compared the results obtained with moving average (MA) and NN. ANN model (55.1%) was found to be significantly better than MA model (50.4%).

Kara *et al.* (2011) developed two efficient models and compared the models' performances in predicting daily BIST-100 Index direction. Their models were based on two classification techniques, ANN and support vector machines (SVM). Ten technical indicators were selected as inputs of the proposed models. Two comprehensive parameter setting experiments for both models were performed to improve their prediction performances. Experimental results showed that average performance of ANN model (75.74%) was significantly better than SVM model (71.52%).

3. CONSTRAINTS OF THE STUDY

Global economic crises affect the real and financial markets of all countries at different rates. One of the basic constraints of the present study is that it is based on BIST-100 index data during the 2007-2009 crisis. Another constraint is related with the variables used in the present predictive ANN model since there is not a gold standard about the variables to be employed.

4. MATERIALS AND METHODS

In this study it is aimed to predict the status of BIST-100 index both for the next day and next week by the aid of ANN in the global economic crises terms. For this purpose feed forward back propagation networks are used. For training, a set of data that is obtained from 30 months (July 2007 – December 2009) is used. These data is obtained from Turkish Central Bank database composed of the variables namely gold price, oil price, interest rate, consumer price index (CPI), exchange rate, money supply and BIST volume. The summarized data are presented in Table-8. The training data set is composed of 12 months (July 2007 – June 2008) and the test data set that is composed of 18 months (July 2008 – December 2009). The topology of the network is composed of 1 input layer, 2 hidden layers and 1 output layer. The number of neurons at each layer are 7, 9, 7, and 2 respectively and given in Figure 1 (Öztemel, 2003; Karaoglan, 2011).

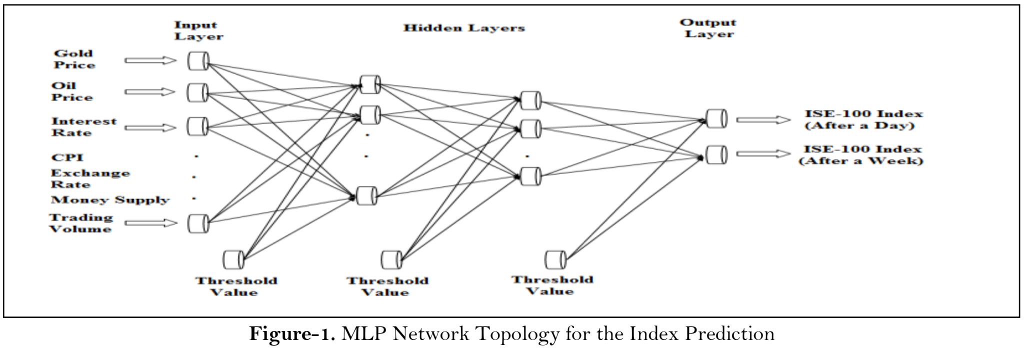

Figure-1. MLP Network Topology for the Index Prediction

For the neurons of input layer Purelin function is used as the activation function while tangent sigmoid function is used for the other neurons at each layer. The structures of these functions are presented in Figures-2(a) and 2(b).

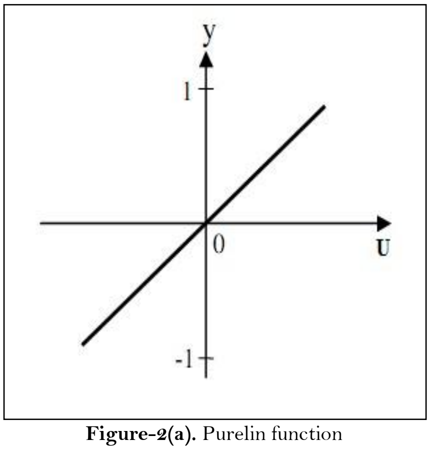

Figure-2(a). Purelin function

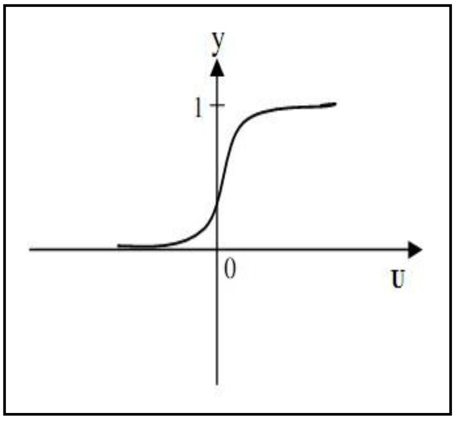

Figure-2(b). Tangent sigmoid function

Purelin fuction can be defined in two different types such as, $U=\sum_{i=1}^{n}x_i w_i+\theta$ or $U=\sum_{i=1}^{n}x_i w_i-\theta$ and $Y=f(U)=AU$, where A is constant, θ is the threshold value and U is the sum of the net input. Tangent sigmoid can be represented as $y=f(U)=\frac{1}{1+e^{-U}}=\frac{1}{2}\left[\tanh\left(\frac{U}{2}\right)-1\right]$.

All the columns are divided to their max value and by this way the data is coded as the biggest value of each column is 1. Gradient descent is used as the training algorithm. To find the suitable network topology, response surface methodology (RSM) is used. RSM is one of the well-known designs of experiment technique which is used for modeling the relationship between the input variables (factors) and the output variable (response) by using minimum number of experimental results. By this way it is possible to optimize the system parameters or to predict the response of unpracticed combinations of different factor levels (Demirtas and Aslan Deniz, 2012). By using RSM the optimum combination of learning coefficient (*lr*) and the momentum coefficient (*mc*) that has the minimum square error (*mse*) is searched.

The training of the ANN is performed by using Matlab R2008b. The pseudocode for the given ANN is coded as:

By preliminary experiments learning coefficient (***lr***) is decided to be between 0.01 – 0.009 and momentum coefficient (***mc***) is between 0.2 – 0.9 ranges. By using these ranges the experimental design that is composed of 9 experimental runs is designed by using central composite face centered design with 1 center point by the aid of Minitab statistical package. For the each combination of *lr* and *mc*, the ANN is trained and the *mse* values of each training run is recorded and presented in Table-1.

```
Define the input matrix (P0) and calculate its transpose (P)
Define the output matrix (T0) and calculate its transpose (T)
Define the number of neurons of the input layer (S0)
Define the number of neurons of the hidden layers (S1, S2)
Define the number of neurons of the output layer (S3)
Construct the network topology and start to traing by using the given code below:
[Pn,minP,maxP,tn,minT,maxT] = premnmx(P,T);
[Net = newff(minmax(P), [S0,S1,S2,S3],(!!! INVALID CITATION !!!),
'traingd');
net.trainParam.epochs = 80000;
        net.trainParam.goal = 0.001;
        net.trainParam.show = 5000;
        net.trainParam.mc = ;     %Will be determined by RSM
        net.trainParam.lr  =  ;    % Will be determined by RSM
        net.trainParam.lr_inc = 1.01;
        net = train(net,P,T);
Eğitim Sonucunu Kaydet
```

The *mse* column represents the *mse* value observed after the Matlab training, and the fitted *mse* represents the predicted *mse* value by using the mathematical equations given in Equation (1).

Table-1. Design of experiment for *lr* ve *mc* coefficients

Number of experimental run	*lr*	*mc*	*mse*	*Fitted mse*
1	0.0090	0.200	0.00254	0.002496
2	0.0100	0.200	0.00291	0.002928
3	0.0090	0.900	0.00360	0.003068
4	0.0100	0.900	0.00248	0.002010
5	0.0090	0.550	0.00360	0.004176
6	0.0100	0.550	0.00341	0.003862
7	0.0095	0.200	0.00507	0.005096
8	0.0095	0.900	0.00392	0.004922
9	0.0095	0.550	0.00743	0.006402

Equation (1) represents the mathematical relationship between the factors (*lr*, *mc*) and the response (*mse*) that is calculated by using the values given in Table-1 with the aid of RSM.

$$mse = -0.87 + 181.99(lr) + 0.03(mc) - 9533.33(lr)^2 - 0.01(mc)^2 - 2.13(lr)(mc) \quad (1)$$

The R^2 value (coefficient of determination) is calculated as 83.75 % and this means that the *lr* and *mc* highly explains the variation at *mse*. The surface plot of Equation (1) is given in Figure-3.

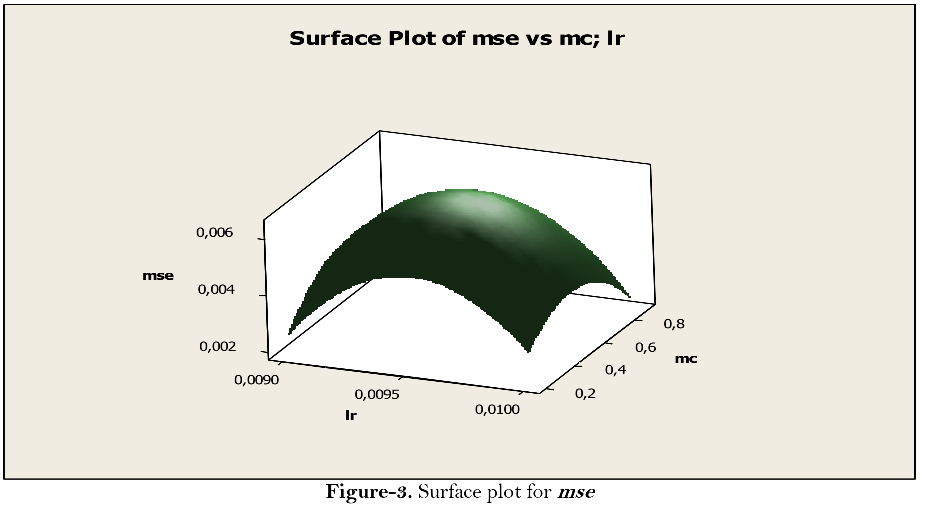

Figure-3. Surface plot for ***mse***

When the Figure-3 is examined it is observed that it is possible to reduce the *mse* by reorganizing the minimum and maximum levels of *lr* and *mc*. For this purpose factor levels for *lr* and *mc* are shifted to [0.05-0.09] and [0.2-0.05] respectively. The default of central composite design is used for experimental design is performed. The results and the mathematical equation derived from these results are given in Table-2 and Equation (2) respectively.

Table-2. Second design for *lr* and *mc* coefficients

Number of experimental run	*lr*	*mc*	*mse*	*Fitted mse*
1	0.0500	0.050	0.00182	0.001660
2	0.0900	0.050	0.00100	0.000750
3	0.0500	0.200	0.00136	0.000930
4	0.0900	0.200	0.00254	0.002020
5	0.0417	0.125	0.00100	0.001276
6	0.0983	0.125	0.00100	0.001404
7	0.0700	0.019	0.00100	0.001149
8	0.0700	0.231	0.00100	0.001531
9	0.0700	0.125	0.00111	0.001110

$$mse = 0.005372 - 0.079667(lr) - 0.026644(mc) + 0.287500(lr)^2 + 0.020444(mc)^2 + 0.333333(lr)(mc) \quad (2)$$

The surface plot for Equation (2) is given in Figure-4. In this stage it is required to find the optimum *lr* and *mc* values those gives the minimum *mse* value. For this purpose minitab response optimizer module is used for optimization. This module uses gradient descent method for searching the target value.

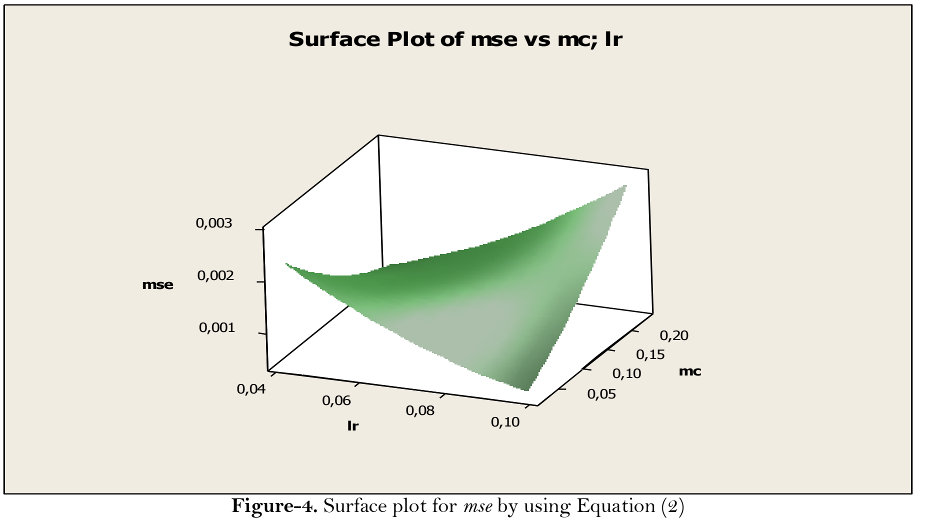

Figure-4. Surface plot for *mse* by using Equation (2)

The optimum values for *lr* and *mc* are calculated as 0.0417 and 0.2311 and given in Figure-5.

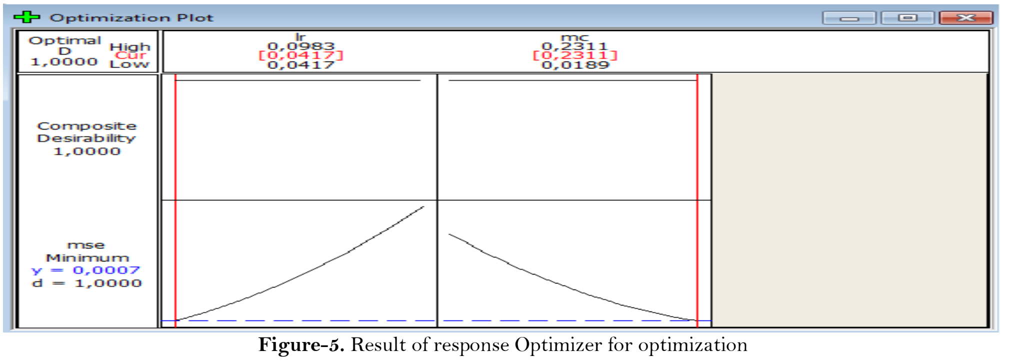

Figure-5. Result of response Optimizer for optimization

According to Figure-5 it is clearly observed that the *mse* value is minimized and predicted to be 0.0007 for the calculated optimum factor combination. This value is lower than the target *mse* of 0.001. For the optimum values of *mc* and *lr* the training performance of the ANN is given in Figure-6.

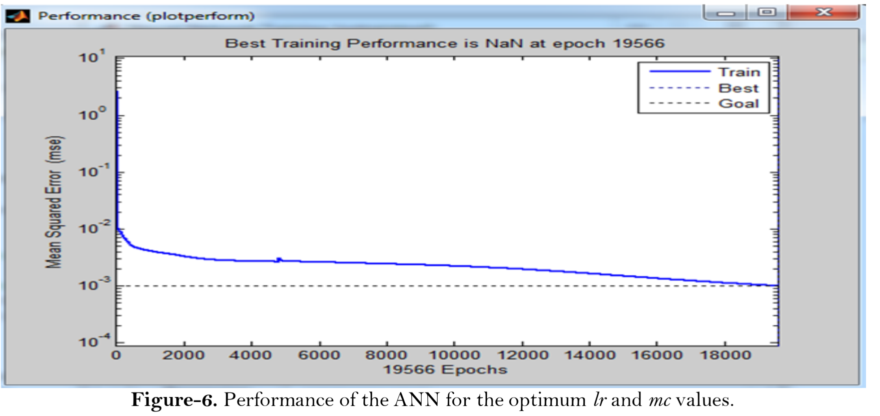

Figure-6. Performance of the ANN for the optimum *lr* and *mc* values.

According to the Figure-6, it is observed that the training is completed successfully at 18000 iterations. In the next section, the trained ANN is tested for the test data set.

5. TEST RESULTS AND THE DISCUSSIONS

In this study the ındex values observed between July 2008 – December 2009 are used as the test values. The trained network is tested for the values given in Table 8 and for the values of 7 factors (gold price, oil price, interest rate, CPI, exchange rate, money supply and BIST volume) measured at the end of the month; the index is predicted for the next day and next month at the crisis environment. The test results are given in Table-3.

Table-3. BIST-100 Index prediction at the crisis environment

Years	Months	(A) ISE–100 Index (Value of the next day)	(B) Predicted value of ISE–100 Index with ANN (for the next day)	(C) =|A-B|/A Error	(D) ISE–100 Index (Value of the next week)	(E) Predicted value of ISE–100 Index with ANN (for the next week)	(F) =|D-E|/D Error
	July	42984.66	43145	0.00373	41627.66	42254	0.01505
	August	39456.77	38348	0.02810	39115.63	37952	0.02975
	September	34553.00	35643	0.03155	30772.63	31926	0.03748
							Continue
	October	27987.65	27548	0.01571	26648.17	26147	0.01881
	November	24331.78	24326	0.00024	24034.70	23845	0.00789
2008	December	27005.63	26982	0.00088	27892.65	26748	0.04104
	January	25270.81	25168	0.00407	26735.21	26145	0.02208
	February	23699.93	22645	0.04451	23220.02	22148	0.04617
	March	25943.57	24982	0.03706	26377.63	25124	0.04753
	April	32170.71	31963	0.00646	32842.61	32315	0.01606
	May	36001.65	36521	0.01443	34750.19	35345	0.01712
	June	37245.86	38345	0.02951	36758.82	38446	0.04590
	July	44613.74	45458	0.01892	44767.58	45645	0.01960
	August	46935.62	47852	0.01952	45273.98	46254	0.02165
	September	47804.39	48956	0.02409	49466.05	50732	0.02559
	October	47456.11	45932	0.03212	46969.89	45145	0.03885
	November	46083.95	48052	0.04271	49915.76	52148	0.04472
2009	December	53368.16	52874	0.00926	54972.94	54387	0.01066
			Mean Error	0.02015		Mean Error	0.02811

The predictions are performed for July 2008 and December 2009. In this time window the crisis was hard for the second quarter of 2008 and the first quarter of 2009. Also the crisis was getting ease off at the last third quarter of 2009. The prediction errors between the observed values are given in (C) and (F) columns. When this error values are examined the overall error rate for the 18 month period is lower that 5%. This results shows that the trained ANN has the ability of accurate prediction for the samples that is not used at training phase. The prediction errors for the index values of next day is ranged between 0.00024 - 0.04451; and the prediction errors for the index values of next month is ranged between 0.00789 - 0.04753. Also the overall mean prediction error for the next day and next month are calculated as 0.02015 (2.02%) and 0.02811 (2.81%) respectively.

6. PREDICTED VALUES COMPATIBILITY TEST USING REAL DATA SETS.

In order to test the compatibility with real data and the predicted value with ANN intended for BIST-100 Index, IBM SPSS 20 package program T-test was used in the present study. Kolmogorov-Smirnov (K-S) test had been used earlier in order to show normal distribution of the data sets compared. K-S test of the **next day** Index value for the real data sets is 0.790 and for the estimated values with ANN 0.749. As these significance values are higher than 0.05, both data sets compared have a normal distribution (Table-4). According to the T-test results, t-statistic is -0.453 and the significance value corresponding to this value is 0.656 (Table-5). These results indicate that there is no statistically significant difference in predicted values and real values averages at a significance level of 5%.

Table–4. Kolmogorov-Smirnov normality test for the next day value of the Index

Hypothesis Test Summary			
Null Hypothesis	**Test**	**Sig.**	**Decision**
The distribution of Index Value _for_The_Next_Day is normal with mean 36.828,56 and standard deviation 9.650,30.	One-Sample Kolmogorov-Smirnov Test	,790	Retain the null hypothesis
			Continue
The distribution of Obtained Value_with_ANN_for_Day is normal with mean 36.930,00 and standard deviation 9.987,43.	One-Sample Kolmogorov-Smirnov Test	,749	Retain the null hypothesis

Asymptotic significances are displayed. The significances level is ,05.

Table–5. Comparison between the estimated value and the next day value of the Index

Pair 1	Paired Differences 95% Confidence Interval of the Difference Lower	 Upper	t	df	Sig. (2-tailed)
BIST-100 value that estimated with ANN for the next day	-573.82922	370.93922	-.453	17	.656

K-S test of the **next week** Index value for the real data sets is 0.846 and for the estimated values with ANN 0.727. As these significance values are higher than 0.05, both data sets compared have a normal distribution (Table-6). According to the T-test results, t-statistic is -0.114 and the significance value corresponding to this value is 0.911 (Table-7). These results indicate that there is no statistically significant difference in predicted values and real values averages at a significance level of 5%.

Table-6. Kolmogorov-Smirnov normality test for the next week value of the Index

Hypothesis Test Summary			
Null Hypothesis	**Test**	**Sig.**	**Decision**
The distribution of ObtainedValue_with_ANN_for_Week is normal with mean 36.817,00 and standard deviation 10.579,90.	One-Sample Kolmogorov-Smirnov Test	,727	Retain the null hypothesis
The distribution of IndexValue _for_The_Next_Week is normal with mean 36.785,67 and standard deviation 10.076,12.	One-Sample Kolmogorov-Smirnov Test	,846	Retain the null hypothesis

Asymptotic significances are displayed. The significances level is ,05.

Table–7. Comparison between the estimated value and the next week value of the Index

Pair 2	Paired Differences 95% Confidence Interval of the Difference Lower	 Upper	t	df	Sig. (2-tailed)
BIST-100 value that estimated with ANN for the next week	-612.18191	549.52857	-.114	17	.911

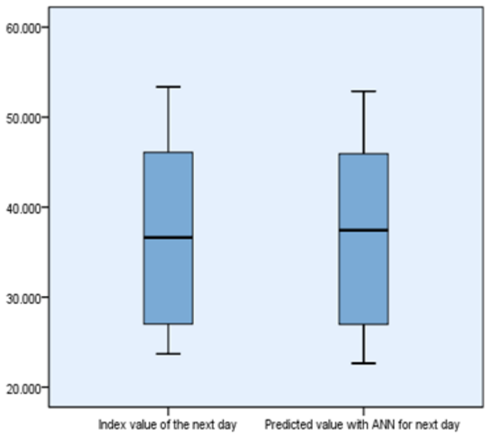

Figure-7(a). Distributions of the estimated value and the next day value of the Index

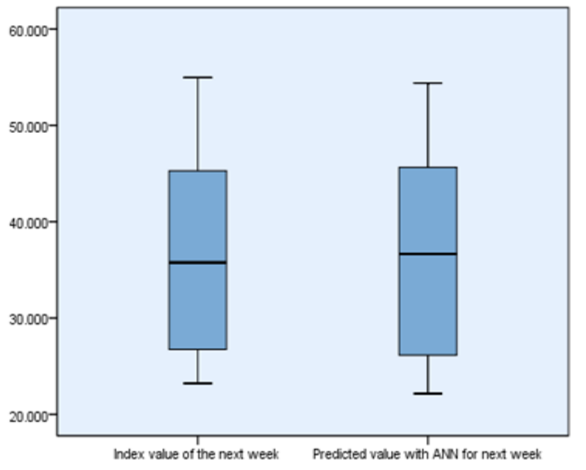

Figure-7(b). Distributions of the estimated value and the next week value of the Index

In Figure-7(a), it is obvious that the averages of predicted values and real values for the next day are very close to each other. This implies that ANNs are quite successful in estimating the index value of the next day. Similarly, in Figure-7(b), it is obvious that the averages of predicted values and real values for the next week are very close to each other indicating that ANNs are quite successful in estimating the index value of the next week. In general, ANNs can predict the direction of BIST-100 Index for the next day and the next week during and after the economic crisis.

7. CONCLUSIONS AND FUTURE WORKS

In this study, BIST-100 index predictability during July 2007-December 2009 crisis has been investigated using ANN. According to the results, ANN is quite successfully in predicting Index direction. The results obtained also suggest that ANN can foresee next day and next week values with an accuracy margin error of less than 5% even for unknown samples. Future studies may focus on next month predictability. Moreover, different studies can be considered by increasing the number of input variables or/and by using different input variables. If the findings of the present study are assessed with other related studies; ANN model in predicting BIST-100 Index demonstrated that the results obtained were quite close to the real market results. This outcome is very important for investors, especially in periods huge economic fragility like financial crises. Hence, especially institutional investors and portfolio managers can use neural networks in their investment in their portfolio preferences.

REFERENCES

Aghababaeyan, R., K. Najeeb Ahmad and S. Tamanna, 2011. Forecasting the Tehran stock market by artificial neural network. International Journal of Advanced Computer Science and Applications, Special Issue on Artificial Intelligence: 13-17. Available from http://dx.doi.org/10.14569/SpecialIssue.2011.010303#sthash.YWRIBxW0.dpuf.

Akel, V. and M.F. Bayramoğlu, 2008. Kriz dönemlerinde yapay sinir ağları ile finansal ongörüde bulunma: İMKB-100 endeksi Örneği. In International Symposium on International Capital Flows and Emerging Markets, Turkey: 24-27.

Demirtas, M. and K. Aslan Deniz, 2012. Optimization of PI parameters for DSP-based permanent magnet brushless motor drive using response surface methodology. Energy Conversion and Management, 56: 104-111.

Desai, J., A. Trivedi and N.A. Joshi, 2012. Forecasting of stock market indices using artificial neural network. Shri Chimanbhai Patel Institutes, Ahmedabad Working Paper No. CPI/MBA/2013/0003.

Diler, A.İ., 2003. İMKB Ulusal 100 endeksinin yönünün Yapay Sinir Ağları: Hata Geriye Yayma Yöntemi ile Tahmin Edilmesi. Türkiye'de Banklar, Sermaye Piyasası ve Ekonomik Büyüme: Koentegrasyon ve Nedensellik Analizi (1989-2000), 81.

Gençtürk, M., 2009. Finansal Kriz dönemlerinde makroekonomik faktörlerin hisse senedi fiyatlarına Etkisi. Suleyman Demirel University Journal of Faculty of Economics & Administrative Sciences, 14(1): 127-136.

Guresen, E., G. Kayakutlu and T.U. Daim, 2011. Using artificial neural network models in stock market index prediction. Expert Systems with Applications, 38(8): 10389-10397.

Kara, Y., M.A. Boyacioglu and Ö.K. Baykan, 2011. Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul stock exchange. Expert Systems with Applications, 38(5): 5311-5319.

Karaoglan, A.D., 2011. An integrated neural network structure for recognizing autocorrelated and trending processes. Mathematical & Computational Applications, 16(2): 514-523.

Kimoto, T., K. Asakawa, M. Yoda and M. Takeoka, 1990. In: Stock market prediction system with modular neural network. Proceedings of the International Joint Conference on Neural Networks. pp: 1-6.

Kutlu, B. and B. Bertan, 2009. Yapay Sinir Ağları ile Borsa Endeksi Tahmini. Yönetim, İstanbul Üniversitesi İşletme Fakültesi İşletme İktisadi Enstitüsü Dergisi, 20(63): 25-40.

Li, F. and C. Liu, 2009. Application study of BP neural network on stock market prediction. Ninth International Conference on Hybrid Intelligent Systems. IEEE, pp: 174-178.

Mallaris, M. and S. Linda, 1996. Using neural networks to forecast the S&P 100 implied volatility. Neurocomputing, 10(2): 83-195.

Mizuno, H., M. Kosaka, H. Yajima and N. Komoda, 1998. Application of neural network to technical analysis of stock market prediction. Studies in Informatic and Control, 7(3): 111-120.

O'connor, N. and G.M. Michael, 2005. A neural network approach to predicting stock exchange movements using external factors. Knowledge-Based Systems, 19(5): 371-378.

Oh, K.J., T.Y. Kim and C. Kim, 2006. An early warning system for detection of financial crisis using financial market volatility. Expert Systems, 23(2): 83-98.

Öztemel, E., 2003. Yapay sinir ağları. İstanbul: Papatya Yayıncılık.

Phua, P.K.H., D. Ming and W. Lin, 2000. Neural network with genetic algorithms for stocks prediction. Fifth Conference of the Association of Asian-Pacific Operations Research Societies Proceedings, 5th - 7th July, Singapore.

Vural Barış, B., 2007. Yapay sinir ağları İle finansal tahmin. Yüksek Lisans Tezi, Ankara Üniversitesi Sosyal Bilimler Enstitüsü, İşletme Anabilim Dalı, Ankara.

Wang, J.Z., J.J. Wang, Z.G. Zhang and S.P. Guo, 2011. Forecasting stock indices with back propagation neural network. Expert Systems with Applications, 38(11): 14346-14355.

Yıldız, B., 2001. Finansal Başarısızlığın Öngörülmesinde Yapay Sinir Ağı Kullanımı ve Halka Açık Şirketlerde Ampirik Bir Uygulama. İMKB Dergisi, 5(17): 51-67.

Yildiz, B., A. Yalama and M. Coskun, 2008. Forecasting the Istanbul stock exchange national 100 index using an artificial neural network. World Academy of Science, Engineering and Technology, 46: 36-39.

Yoon, Y. and S. George, 1991. Predicting stock price performance: A neural network approach. Proceedings of the 24th Annual Hawaii International Conference on System Sciences, 4: 156-162.

Yoon, Y., G. Swales and T.M. Margvio, 1993. A comparison of discriminant analysis versus artificial neural networks. Journal of the Operational Research Society, 44(1): 51-60.

BIBLIOGRAPHY

Choi, J.H., M.K. Lee and M.W. Rhee, 1995. Trading S&P 500 stock index futures using a neural network. The Proceedings of the Third Annual International Conference on Artificial Intelligence Applications on Wall Street: pp: 63-72.

Şenol, D. and Ö. Meltem, 2010. Stock price direction prediction using artificial neural network approach: The case of Turkey. Journal of Artificial Intelligence, 1(2): 70-77.

APPENDIX-1.

Table–8. Table of Data

Years	Months	Independent Variables (Inputs)							Dependent Variables (Outputs)	
		Gold Prices	Oil Prices	Interest Rate	CPI	Exchange Rate	Money Supply	Trading Volume	BIST-100 Index (After a Day)	BIST-100 Index (After a Week)
2007	July	664.00	72.56	22.30	138.67	1.307	23735838	1961542.4	51299.3	50708.2
	August	665.87	69.70	22.08	138.70	1.331	23897573	1887848.2	49936.9	49050.4
	September	724.34	77.43	22.03	140.13	1.216	24476332	1661433.1	54198.0	56792.9
	October	759.72	84.76	21.66	142.67	1.192	25161002	2242536.5	57371.3	56076.4
	November	803.30	85.72	21.00	145.45	1.190	24655080	1898404.0	54320.0	56490.5

	December	805.25	90.70	21.03	145.77	1.170	26072505	575205.6	54708.4	52569.5
2008	January	886.56	87.92	21.15	146.94	1.178	25154851	1404939.5	44452.0	41866.4
	February	931.60	96.35	21.22	148.84	1.182	24773441	1601604.2	43343.5	42523.8
	March	959.00	98.63	21.12	150.27	1.283	26581454	1253735.4	40674.1	42277.1
	April	908.38	107.33	21.12	152.79	1.284	27611879	1296326.7	42664.3	43272.4
	May	887.95	121.68	21.62	155.07	1.221	26991182	168143.0	40121.1	39645.5
	June	895.88	136.03	22.66	154.51	1.230	27790336	926565.9	33208.2	35010.0
	July	943.56	122.48	23.05	155.40	1.191	28236378	2717498.2	42984.6	41627.6
	August	841.70	111.23	22.97	155.02	1.188	27776260	815395.3	39456.7	39115.6
	September	832.56	90.32	23.86	155.72	1.238	31974600	476729.3	34553.0	30772.6
	October	791.26	57.43	24.98	159.77	1.504	30600476	1908962.7	27987.6	26648.1
	November	768.06	47.22	25.67	161.10	1.573	31196449	1336259.8	24331.7	24034.7
	December	803.75	35.58	25.68	160.44	1.520	30468001	972079.3	27005.6	27892.6
2009	January	870.15	42.02	20.32	160,90	1.619	29049120	885158.1	25270.8	26735.2
	February	947.38	43.23	18.29	160.35	1.689	30579954	927823.4	23699.9	23220.0
	March	935.50	46.65	18.17	162.12	1.696	31909720	1107188.5	25943.5	26377.6
	April	894.33	50.36	17.49	162.15	1.605	31759158	2668675.4	32170.7	32842.6
	May	942.94	63.71	17.36	163.19	1.570	31302568	2543817.1	36001.6	34750.1
	June	944.19	69.56	17.42	163.37	1.538	32137996	2147340.2	37245.8	36758.8
	July	934.75	68.59	17.01	163.78	1.484	31248103	3277447.2	44613.7	44767.5
	August	954.38	70.37	16.84	163.29	1.497	31994514	1971392.2	46935.6	45273.9
	September	1000.19	65.55	16.55	163.93	1.489	34843833	2667545.1	47804.3	49466.0
	October	1040.55	75.56	15.67	167.88	1.489	33256841	3023312.2	47456.1	46969.8
	November	1113.67	76.21	15.62	170.01	1.490	38915183	886238.1	46083.9	49915.7
	December	1130.19	77.16	15.67	170.91	1.513	35251149	2617335.5	53368.1	54972.9