İşletme Araştırmaları Dergisi
ISSN: 1309 - 0712

Journal Of
Business Research
Turk
www.isarder.org

Forecast Share Prices with Artificial Neural Network in Crisis Periods

Feyyaz ZEREN
Sakarya University
Faculty of Management
Sakarya,Turkey
feyyazzeren@outlook.com

Oylum Şehvez ERGÜZEL
Sakarya University
Master Student in International Trade
Sakarya, Turkey
oerguzel@sakarya.edu.tr

Abstract

Crisis periods present quite a significant moment for financial markets. Considering not losing and changing the crisis periods into opportunities, forecasts of share prices during these periods have an importance for the investors. In this study, daily closing prices of Borsa Istanbul National 100 index during the three big crisis periods, as 1994, 2001, and 2008, have been tried to be forecasted, by using artificial neural networks. As a result of this study, it is determined that in the forecasts of Borsa Istanbul, artificial neural networks show high performance. This result was proved by both comparing the values that occurred and forecasted on the graphics, and Mean Absolute Percentage Error (MAPE) calculations.

Keywords: Artificial Neural Networks, Borsa Istanbul, Forecasting, Crisis Periods

Introduction

When Turkey's economic history is considered, it is seen as an inevitable fact that there occurs an economic crisis every 10 years, and these crises should be studied by many different analysing techniques. The hyperinflation that occurred in 1994 for the first time is one of those crises. That the public deficit had dramatically risen, interest rates had risen and the currency is doubled are the most explicit signs of that economic crisis. One of the other biggest crises of Turkish economic history is the one political crisis between the president Ahmet Necdet Sezer and the prime minister Bulent Ecevit, also called as 'Black Wednesday', that happened in the National Security Council meeting in February 2001. This argument turned out to be the economic crisis that took hold of all Turkey. What should be mentioned as the last is the global financial crisis in 2008 that took hold over the world and showed a domino effect. In other words, with is well known name, it is 'Mortgage Crisis'. That American banks applied wrong credit strategies, they allowed the poor to get subprime mortgage, derivative transactions of those credits, and the difficulties faced while paying back those credits in property market have formed the main points of this crisis (Göçer, 2012). Not only those, but there are many small or big scale crises to be mentioned among the economic crises of the last 20 years. Some of them, which are thought to have a great effect in Turkey's economic structure in the past, are as follows; 97 Asia economic crisis, 99 Marmara earthquake and 2013 Taksim Gezi Park incidents.

The common point of all is the fact that while crisis period is a big destruction for some, for the others it means big opportunities. In this sense, forecasting of the changes in share prices during the crisis periods has a great importance for the investors. For this, making forecasts correctly is significant in planning the future and making decisions. The more correct the forecasts are, the more profitable will be the investment decisions of people who made forecastings (Hadavandi et. al. 2010). With the economic structures' going global, not only local dynamics but also international economic events have started to be effective on the countries' stock markets. In this context, the risks of shares that are in interaction with local and global developments, economic conditions, and investor expectations, are quite high. For this, if the prices are forecasted in a correct way, the incomes of the shares will be high (Karaatli et. al., 2005).

Multiple regression, ARCH/GARCH models, early warning systems, genetical algorithms and fuzzy logic are some of the strategies used in share prices forecasting. Along with these, one other main forecasting system for share prices is artificial neural networks. Artificial neural networks (ANN) do not contain standard formulas like econometric models, and they can adapt to the changes in the market easily (Guresen et. al., 2011). One other advantage of this technique is that it is in appropriate form for nonparametric and nonlinear time series (Khashei and Bijari, 2011). Considering the fact that financial time series behave in a nonlinear way, ANN is determined as an appropriate technique for forecasting share prices which are a financial time series.

Artificial Neural Networks

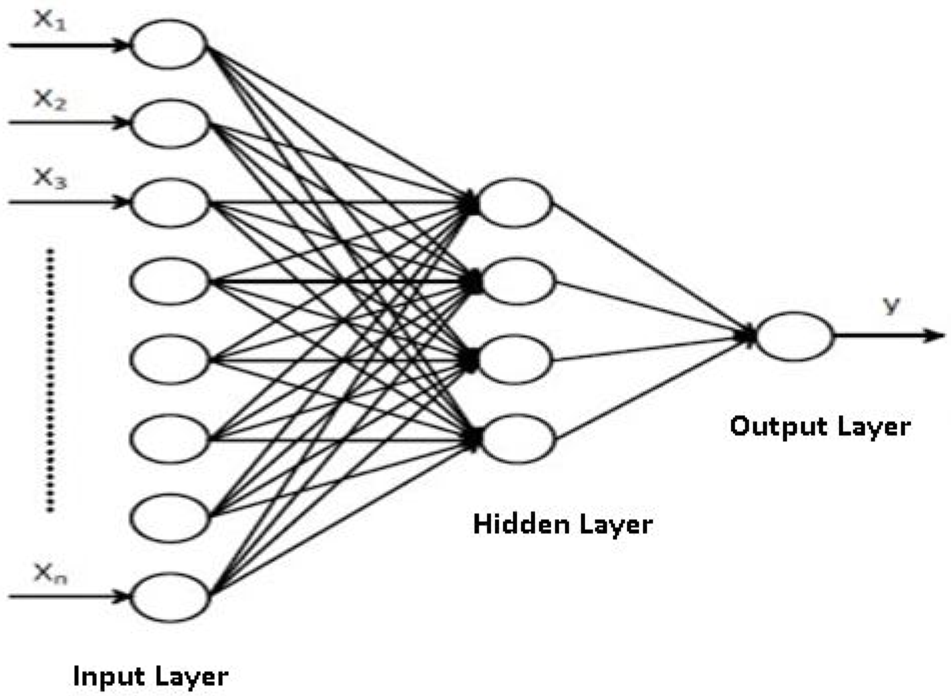
The human brain can be considered as the most complicated machine in the world. While computers can solve many numbers of complex problems, they are quite insufficient in identifying and using information gained with experiences. Although we are quite far away than developing a system that works completely like human brain; still, there are some systems getting into our lives, which can partially copy the human brain. Today, so many products, from unmanned automobiles to servant robots, have been manufactured as a result of these studies (Birgili et. al, 2013). As the subbranches of the artificial intelligence, the systems such as Expert Systems, Fuzzy Logic, Genetical Algorithms and Artificial Neural Networks are the engineering methods that can react according to the human behaviors (Elmas, 2003).

ANN is a data processing system that has been formed inspired by biological neural networks, that copies the humain brain system in a basic way and that shows similarities to biological neural networks (Kaynar and Taştan, 2009). In other words, ANN finds solutions for the problems that normally require the natural human skills towards thinking and observing. The main reason that a human can find solutions to problems that require thinking and observing skills is the ability of the human brain, thus the human as well, to learn by living or trying. ANN forms its own experiences by the information it gained from the examples, and then, in similar subjects it makes similar decisions (Erkaymaz and Yasar, 2011). ANN is a broadcast data processing system that cooperates in a parallel way, and each having its own data processing skills and memory. The most significant feature of artificial neural networks is its ability to learn (Yıldız, 2009). Thanks to this feature, ANN is successfully applied in many areas such as industry, business, finance, meteorology, education, military, defence and health.

ANNs are mathematical processes that are constituted from many process elements which have been weighted and tied together. A process element is indeed an equation that is frequently called as transfer function. This process element takes the signals from other neurons, combines and changes them, and then finds out a numerical result. In general, process elements almost correspond to real biologic neurons and they tie up together in a net. It is this structure that forms neural networks (Yurtoğlu, 2005).

ANN is formed with three layers. These are input layer, output layer and hidden layer. The modelling of the artificial neural networks is done by the data from the education and test.Education data is formed of education input and output; on the other hand, test data is formed of only test input. The formed model tries to forecast the test output by using the learning process that it required durin education period. Here, the input data is similar to independent variables in the statistics and the output data is similar to dependent variables. The other layer is the hidden one. The neurons in the hidden layer have no connection to the outside environment.They only take the signals from input layer and send those signals to the output layer. When it is compared to the econometric forecasting, input layer takes the place of mathematical model that makes the forecasting. Choise of the neuron numbers to be in the hidden layer is significant for the performance of the network (Çuhadar and Kayacan, 2005). The general structure of the artificial neural networks is shown in Figure 1.

Figure 1: The General Structure of Artificial Neural Networks



In the education period, the model is taught the relationship structure between the input and the output presented; and in the test period, test outputs are tried to be forecasted regarding the test input. At this point, the input types to be presented to the model are significant. Because, these input variables are the descriptors of the outputs, and with the right input, the chance to get the right results will increase.

Literature Review

When the studies in the literature are considered, artificial neural networks have been used to forecast on forecasting share prices along with financial failures [(Aktaş et. al., 2003) (Benli, 2005) (Altunöz, 2013)], forecasting the changes in the currency [(Yao et. Al., 2000) (Kaynar and Taştan, 2009)], and forecasting the prices of gold (Benli and Yıldız, 2012).

In forecasting the share prices, the techniques such as genetical algorithms and fuzzy logic can be used along with artificial neural networks.

The use of artificial neural systems in the forecasts of Borsa Istanbul was first mentioned in Diler (2003) and Egeli et. al. (2003)'s studies. Within this context, some of the studies in the literature concerning the artificial neural networks and Borsa Istanbul are tried to be explained below.

In their study, Akel and Bayramoglu (2008) tried to forecast the IMKB closing prices during the February 2001 financial crisis period. On the matter whether the model will show a rise or a fall, it is determined to be successful around 73.68%.

In his study on IMKB, Ulusoy (2010) established a neural network system with 13 variables and evaluated it with the algorithm of system's error back-probagation. As a result of the study, it is determined that the model is more successful during the days when there is no increase or decrease. Another factor affecting the model's forecasting power is the political mobility.

In their study in which they worked on 7 companies within the scope of insurance index, Akcan and Kartal (2011) has found that especially in up-to-1-month forecastings, artificial neural networks are successful. In order to forecast the share prices, there were used 4 macroeconomic indicators and 8 balance sheet values as an input.

In another study for forecasts of Istanbul Stock Market, Aygoren et. al. (2012) made a comparison by using both artificial neural networks and Newton Numeric Dialling model. As a result of the study in which the daily data of 15 years, from 1995 to 2010, were used, it is determined that artificial neural networks show a higher performance compared to the other model. Some of the variables (inputs) of this study are interest rates on deposits, gold prices, USD closing prices and interbank market transaction summary.

In Karaatli et. al. (2005)'s study, in which Treasury bill rates, inflation rate (TUFE), industrial production index and currency variables have been used as an input, artificial neural networks and multiple regression models were compared. In the study in which the monthly data of the years between 1990 and 2002 were used, it is determined that the artificial neural networks show a higher performance. In another study making the same comparison, Altay and Satman (2005) again stated that artificial neural networks are showing better performance compared to the multiple regression.

Kutlu and Badur (2009) have formed 3 different models using previous day's index value, dollar currency, overnight interest rate, and the Stock Market of France, Germany, England, Brasil and Japan as inputs to forecast market index via artificial neural networks. Among the formed models, the primary model that consists of previous day's index value, dollar currency and overnight interest rate has provided the strongest forecast. Again, in another study, Avci (2007) tried to forecast Istanbul Stock Market prices regarding the change in transaction volume and market return. According to this study, it is stated that another forecasting model consisting of different variables can be formed.

Apart from these, it is understood from the studies that artificial neural networks are used for the forecasts of other countries' markets. In some of those studies, Olson and Mossman (2002) dealt with Canadian market, Vahedi (2012) with Tahran market, Yoda (1994) with Tokio market, Jang and Lai (1994) with Taiwan market and they tried to forecast the share prices with artificial neural networks. It is possible to encounter many studies like this in the literature. This situation proves that the artificial neural network is a technique that is used globally to forecast the share prices.

The studies in the literature show that ANN shows a high performance in forecasting the share prices. The aim of these studies is to determine whether it is possible to forecast the Borsa Istanbul 100 Index in crisis periods using ANN.

Data and Empirical Findings

Studies show that the price changes in Istanbul Stock Exchange may get affected by a number of variables. However, considering the results of the previous studies, 6 main variables were included to the study as input. These independent variables are; exchange rate, libor (London Interbank Offered Rate), gold's ons price, oil prices and transaction volume. Besides, the closing price of a day prior to the forecasted one was used as an independent variable. Because of the fact that there are daily data used in the study, inflation (TÜFE), which can be seen as a significant variable, was not included in the analyses. What's more, because of the fact that the daily data on gold's ons price can only be traced back to 1997, gold prices were not used in any of the analyses.

In the previous times, forecastes were made with artificial neural networks using monthly data; however, it is seen that the models formed of monthly data are not as effective as the ones formed on daily data. For this reason, our study is based on daily values.

Matlab programme was used during the analyses. The 500 working days before the dates determined as the crisis period constitutes the education data; the beginning date of the crisis and the following 3 months, in other words 50-60 working days (may change depending on the holidays), constitute the test data. Within this context, as it is in most of the previous studies, the ratio between education and test values is determined as 90%-10%. According to the main structure of ANN, the higher the ratio of education data, the more correct results the model will present.

In our study, input layer has 6, output layer has 1, and hidden layer has 2 neurons. As a transferring function in hidden layer, a nonlinear Tangent Hyperbolic Function (tansig) was used. For the analysis of the model, feedforward ANN, which has a great area of usage in the literature, was used. Besides, the neuron number in the hidden layer is determined as 10.

The number of the neurons in the input and output layers is determined according to the requirements of the problem to be dealt with; however, there is not any analytic technique that is developed to give the correct number of neurons to be found in the hidden layer (layers) in means of being optimum. For this reason, only way to deal with the ambiguities in the number of hidden layers and the number of the neurons in those layers is the trial-and-error method [(Efe and Kaynak, 2000) (Çuhadar and Kayacan, 2005)].

In the ANN model, each analysis is carried out in 10000 epochs. Before the data were put into analysis, they were exposed to normalisation process. As a result of this process, every serial is transformed in a way that their values are between 0 and 1, from large to little. After the forecasting is done with ANN, the forecasted test outputs were denormalized. The reason of this transformation is the fact that the forecasted values that turned back to their normal way with denormalisation process can be compared to the real values.

Figure 2: Forecasting of 1994 Economic Crisis

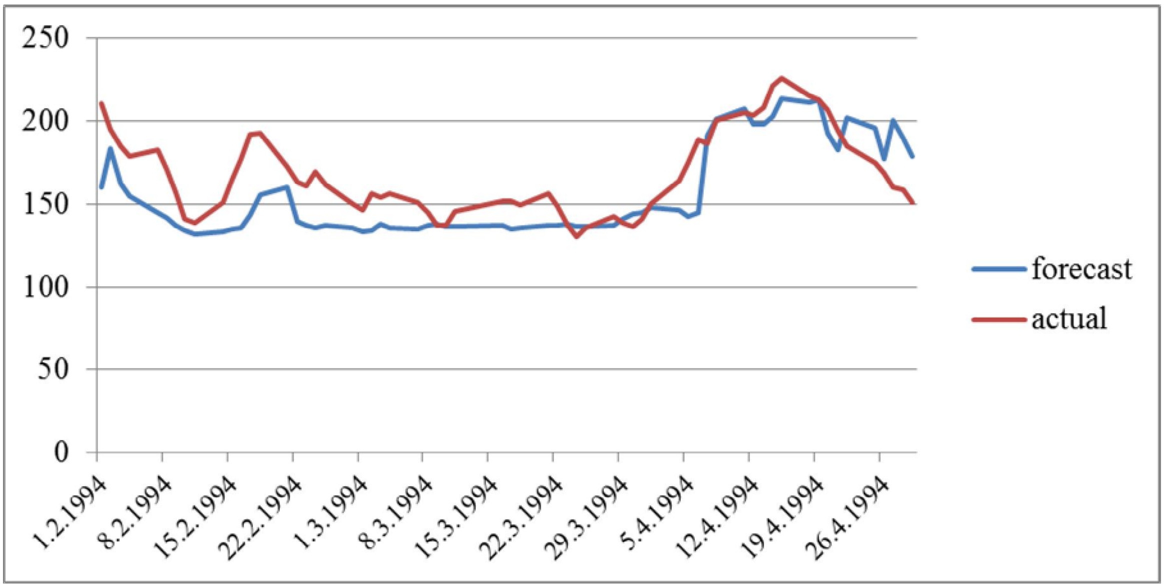


Figure 3: Forecasting of February 2001 Crisis

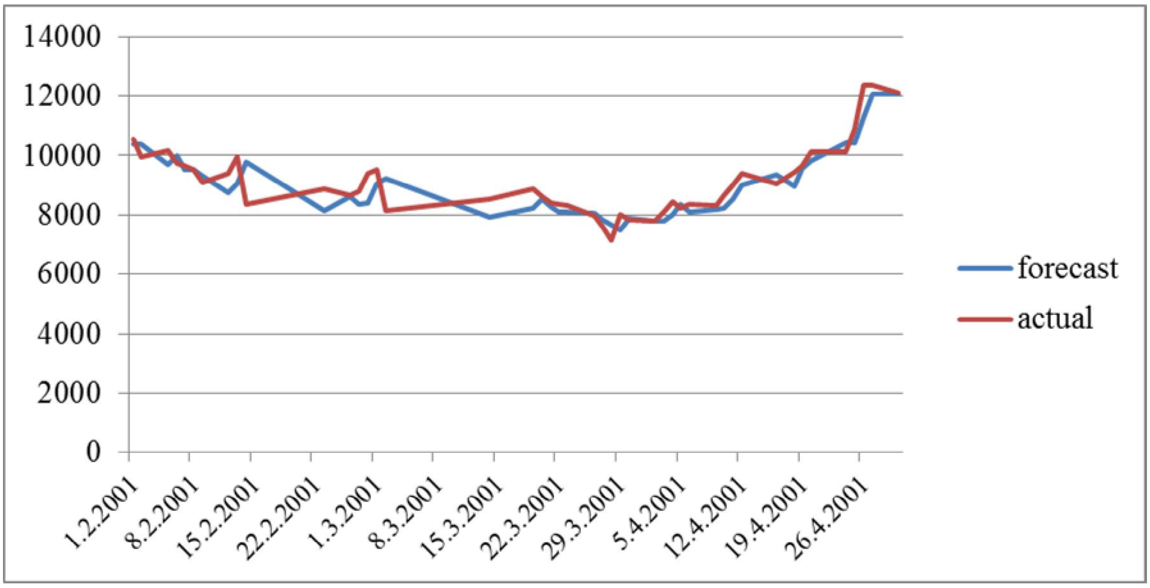
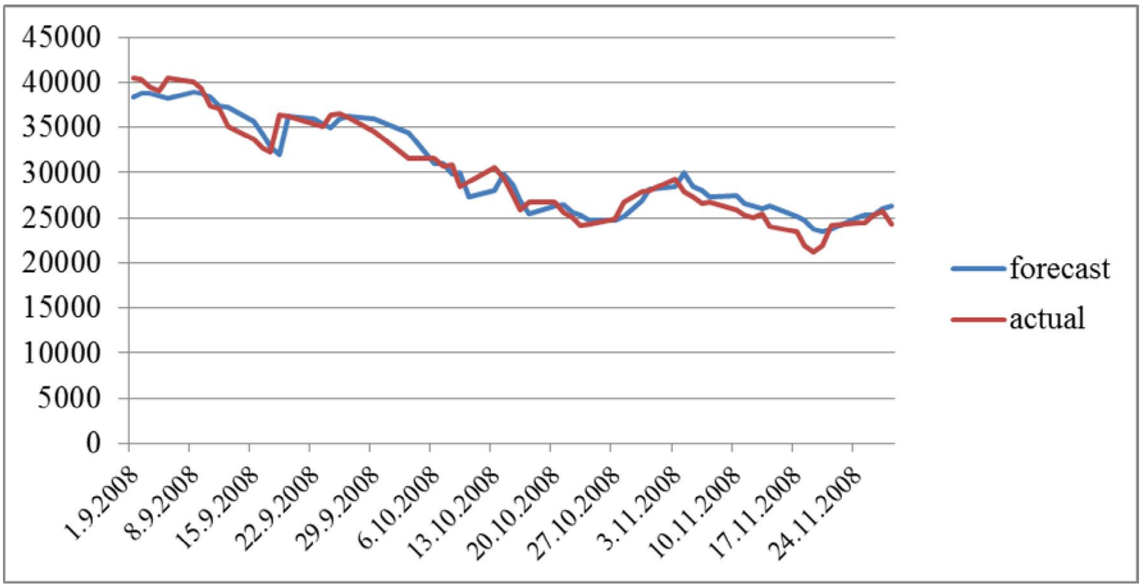


Figure 4: The forecasting of 2008 Global Financial Crisis (Mortgage Crisis)



When Figure 2, 3 and 4, in which the forecasted and real values are compared, are considered, it is seen that ANN has such a great forecasting strength. Moreover, in 2001 and 2008 crises, it is seen that the model has a stronger explanation abilities. Quantitative data regarding these results can be seen in table 2 at end of the paper. One of the reasons of this situation can be seen as the fact that the gold prices were not included in the model on 94 economic crisis. The possibility that data from previous times may be manipulated more may be seen as another cause of this problem. Because, it is not possible to make a correct forecasting with manipulated data.

When evaluating the correctness of the forecast results of the study MAPE (Mean Absolute Percentage Error) techniques are used. This value is calculated as below;

$$MAPE = 100\frac{\sum_{i=1}^{n}\frac{|actual - forecast|}{actual}}{n}$$

Table 1: Performance Standards

	MAPE
1994 Economic Crisis	9.97
February 2001 Crisis	4.31
2008 Mortgage Crisis	3.98

The fact that MAPE values are under 10% in all three crisis periods shows that the model is highly explanatory. It can be seen in many of the studies in the literature that if the MAPE value is under 10%, the model has a high correctness degree [(Witt and Witt, 2000) (Lewis, 2002) (Çuhadar and Kayacan 2005)]. It can be said that the results are within the acceptable limits and forecasts are successful.

Conclusion and Discussion

It is really difficult to forecast the share prices in countries like Turkey which has many manipulative changes in its economic structure. Especially in less developed or developing countries like Turkey, economic and political ambiguities affect macro politics in a dense way. The aim of both the politicians and the investors is to be able to get rid of this. The solution of this is to make forecasts about macroeconomic indicators. The forecasting methods to be used in financial index can be divided into four main categories. These are; technical analysis, basic analysis, traditional time series analysis and lastly artificial intelligence approaches.

In this study, artificial neural networks, from artificial intelligence approaches, are used as a decision support mechanism. In this context, Borsa Istanbul 100 Index was tried to be forecasted by ANN, regarding the 6 local or global, main indicators that has the power to affect Turkish market. The results show that artificial neural networks have a high forecasting ability during the crisis periods. The fact that daily data is used in the study is another element that increases the explanatory power of the model. Besides, MAPE (Mean Absolute Percentage Error) has proved the correctness of the results that were stated by performance standard calculation. All these findings are being supported by many other studies in the literature.

According to all these results, ANN is quite a useful hedging during crisis periods. Thus, individual and corporate investors can make their forecasts pretty close to the real results by using ANN and they can make profitable investments. Another study to be done in the future may be to forecast the share prices of the companies. To be able to do this, along with the macro data used in this study, many micro data that can be provided by the balance sheet data, such as current ratio, liquidity, debt collection period, debt turnover, inventory turnover, ROA and ROE may be used.

References

Akcan, A. and Kartal, C. (2011), "İMKB Sigorta Endeksini Oluşturan Şirketlerin Hisse Senedi Fiyatlarının Yapay Sinir Ağları İle Tahmini", Muhasebe ve Finansman Dergisi,

Akel, V. and Bayramoğlu, M. F., (2008), "Kriz Dönemlerinde Yapay Sinir Ağları İle Finansal Öngörüde Bulunma: İMKB 100 Endeksi Örneği", International Symposium on International Capital Flows and Emerging Markets, Balıkesir, Bandırma, 107–117

Aktaş, R., Doğanay, M., Yıldız B., (2003), "Finansal Başarısızlığın Öngörülmesi: İstatistiksel Yöntemler ve Yapay Sinir Ağı Karşılaştırması", Ankara Üniversitesi SBF Dergisi, Cilt 58, Sayı: 4, 1-24

Altay, E. and Satman, M.H. (2005), "Stock market forecasting: Artificial Neural Networks and Linear Regression Comparison in an Emerging Market", Journal of Financial Management and Analysis, 18(2), 18-33.

Altunöz, U. (2013) "Bankaların Finansal Başarısızlıklarının Diskriminant Analizi ve Yapay Sinir Ağları Çerçevesinde Tahmini", Sakarya Üniversitesi İktisat Dergisi, 2(4), 1-21

Avcı, E. (2007), "Forecasting Daily and Sessional Returns of the ISE-100 Index with Neural Network Models", Journal of Dogus University, 8(2), 128–142.

Aygören, H., Sarıtaş, H., Moralı, T. (2012), "İMKB 100 Endeksinin Yapay Sinir Ağları ve Newton Nümerik Arama Modelleri ile Tahmini", Uluslararası Alanya İşletme Fakültesi Dergisi, 4, 1, 73-88

Benli, Y.K. (2005), "Bankalarda Mali Başarısızlığın Öngörülmesi Lojistik Regresyon ve Yapay Sinir Ağı Karşılaştırması", Gazi Üniversitesi Endüstriyel Sanatlar Eğitim Fakültesi Dergisi, 16, 31-46

Benli, Y.K. and Yıldız, A. (2012), "Altın Fiyatının Yapay Sinir Ağları ve Zaman Serisi Yöntemleri ile Öngörüsü", 16. Finans Sempozyumu, 10-13 Ekim, Erzurum

Birgili, E. Akal, M., Esen, S. (2013), "Bulanık Mantık Yaklaşımıyla Finansal Yönetim Uygulamaları: Bir Literatür Taraması", Uluslararası Yönetim İktisat ve İşletme Dergisi, Cilt 9, Sayı 19

Çuhadar M. and Kayacan C. (2005) "Yapay Sinir Ağları Kullanılarak Konaklama İşletmelerinde Doluluk Oranı Tahmini: Türkiye'deki Konaklama İşletmeleri Üzerine Bir Deneme", Anatolia Turizm Araştırmaları Dergisi, Cilt: 16, Sayı: 1, 24-30

Diler, A.İ. (2003). "İMKB Ulusal-100 Endeksinin Yönünün Yapay Sinir Ağları Hata Geriye Yayma Yöntemi ile Tahmin Edilmesi", İMKB Dergisi, Sayı 25-26, 65-81

Efe, Ö. and Kaynak, O. (2000), "Yapay Sinir Ağları ve Uygulamaları, İstanbul: Boğaziçi Üniversitesi Yayını No: 696.

Egeli, B., Özturan, M., and Badur, B. (2003), "Stock market Prediction Using Artificial Neural Networks", Proceedings of the 3rd Hawaii International Conference on Business, Hawai, USA

Elmas, Ç. (2003), Yapay Sinir Ağları, Seçkin Yayıncılık

Erkaymaz, H. and Yaşar, Ö. (2011), "Yapay Sinir Ağı ile Hava Sıcaklığı Tahmini", 5th International Computer & Instructional Technologies Symposium, 22-24 September, Fırat University, Turkey

Göçer, İ. (2012), "2008 Küresel Ekonomik Krizin Nedenleri ve Seçilmiş Ülke Ekonomilerine Etkileri: Ekonometrik Bir Analiz", Yönetim ve Ekonomi Araştırmaları Dergisi, 17, 18-37

Güresen, E., Kayakutlu, G., Daim, T.U., (2011), "Using Artificial Neural Network Models in Stock Market Index Prediction", Expert Systems with Applications 38, 10389–10397

Hadavandi, E., Shavandi, E., Ghanbari, A. (2010), "Integration of Genetic Fuzzy Systems and Artificial Neural Networks for Stock Price Forecasting", Knowledge-Based Systems 23, 800-808

Jang, G. and Lai, F. (1994), "Intelligent Trading of an Emerging Market", Trading on the Edge, Deboeck, pp. 80-101

Karaatlı, M., Güngör, İ., Demir, Y., Kalaycı, Ş. (2005). "Hisse Senedi Fiyat Hareketlerinin Yapay Sinir Ağları Yöntemi ile Tahmin Edilmesi", Balıkesir Üniversitesi İİBF Dergisi, 2(1), 22-48

Kaynar, O. and Taştan, S. (2009), "Zaman Serisi Analizinde MLP Yapay Sinir Ağları ve Arima Modelinin Karşılaştırılması", Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, Sayı: 33, Temmuz-Aralık 162, 161-172

Khashei, M. and Bijari, M. (2010), "an Artificial Neural Network Model for Time Series Forecasting", Expert Systems with Applications, 37(1), 479–489

Kutlu, B. and Badur, B. (2009), "Yapay Sinir Ağları ile Borsa Endeksi Tahmini", Yönetim. Yıl: 20 Sayı: 63

Lewis, C.D. (1982), Industrial and Business Forecasting Methods, Londra: Butterworths Publishing

Olson, D. and Mossman, C. (2002), "Neural Network Forecasts of Canadian Stock Returns Using Accounting Ratios", International Journal of Forecasting, 1, 1-13

Ulusoy, T. (2010), "İMKB Endeks Öngörüsü İçin İleri Beslemeli Ağ Mimarisine Sahip Yapay Sinir Ağı Modellemesi", International Journal of Economic and Administrative Studies, 3, 5, 21-40

Vahedi, A. (2012), "The Predicting Stock Price using Artificial Neural Network", Journal of Basic and Applied Scientific Research, 2(3)2325-2328

Witt, S.F. and Witt, C.A. (2000), Modeling and Forecasting Demand in Tourism, Londra: Academic Press

Yıldız, B. (2009), Finansal Analizde Yapay Zeka, Detay Yayıncılık

Yao, J., Yili, L., and Tan, C.L. (2000), "Option Price Forecasting Using Neural Networks", Omega, 28, 445-466

Yoda. M, (1994), Predicting the Tokyo Stock Market, Trading on The Edge, Deboeck, 66-79

Yurtoğlu H. (2005), Yapay Sinir Ağları Metodolojisi ile Öngörü Modellemesi: Bazı Makroekonomik Değişkenler İçin Türkiye Örneği; DPT Uzmanlık Tezleri; Yayın No: 2683, Ankara

Table 2: Comparing of Actual and Forecasted Values

	Actual	Forecast		Actual	Forecast
Feb 01, 1994	209.79	133.026	Feb 01, 2001	10546.66	10401.24
Feb 02, 1994	194.63	132.9025	Feb 02, 2001	9952.59	10399.34
Feb 03, 1994	184.88	132.6916	Feb 05, 2001	10187.21	9694.708
Feb 04, 1994	178.95	132.594	Feb 06, 2001	9724.09	10011.54
Feb 07, 1994	182.12	133.5348	Feb 07, 2001	9658.9	9521.151
Feb 08, 1994	170.81	134.9533	Feb 08, 2001	9545.86	9524.38
Feb 09, 1994	156.96	135.9763	Feb 09, 2001	9075.33	9310.232
Feb 10, 1994	140.88	137.3524	Feb 12, 2001	9385.06	8747.175
Feb 11, 1994	138.64	137.0492	Feb 13, 2001	9971.69	9042.868
Feb 14, 1994	150.96	136.7849	Feb 14, 2001	8344.94	9793.514
Feb 15, 1994	164.33	137.7411	Feb 23, 2001	8880.33	8160.632
Feb 16, 1994	176.81	139.493	Feb 26, 2001	8665.88	8630.21
Feb 17, 1994	191.31	139.7799	Feb 27, 2001	8791.6	8377.22
Feb 18, 1994	192.75	139.3945	Feb 28, 2001	9406.65	8406.904
Feb 21, 1994	172.5	140.542	Mar 01, 2001	9513.77	9054.716
Feb 22, 1994	163.18	140.0264	Mar 02, 2001	8150.78	9241.568
Feb 23, 1994	160.65	139.5276	Mar 14, 2001	8522.41	7934.41
Feb 24, 1994	169.27	139.6247	Mar 19, 2001	8860.57	8251.116
Feb 25, 1994	162	140.0168	Mar 20, 2001	8629.21	8545.221
Feb 28, 1994	150.04	141.5073	Mar 21, 2001	8402.85	8282.622
Mar 01, 1994	146.03	140.3935	Mar 22, 2001	8365.64	8114.7
Mar 02, 1994	156.41	141.415	Mar 23, 2001	8331.29	8084.886
Mar 03, 1994	154.09	143.2996	Mar 26, 2001	7959.69	8063.482
Mar 04, 1994	155.92	142.0416	Mar 27, 2001	7614.78	7844.394
Mar 07, 1994	150.89	144.0165	Mar 28, 2001	7159.66	7677.904
Mar 08, 1994	145.06	146.1638	Mar 29, 2001	8022.72	7497.301
Mar 09, 1994	137.05	146.6078	Mar 30, 2001	7855.67	7892.54
Mar 10, 1994	137.31	146.1893	Apr 02, 2001	7806.12	7812.393
Mar 11, 1994	145.11	145.579	Apr 03, 2001	8117.75	7793.958
Mar 16, 1994	151.27	144.2413	Apr 04, 2001	8457.15	8024.945
Mar 17, 1994	151.3	141.3334	Apr 05, 2001	8236.8	8343.787
Mar 18, 1994	149.2	142.4049	Apr 06, 2001	8359.55	8099.051
Mar 21, 1994	155.86	144.1097	Apr 09, 2001	8312.17	8176.75
Mar 22, 1994	148.39	144.1909	Apr 10, 2001	8657.84	8217.005
Mar 23, 1994	136.67	144.6257	Apr 11, 2001	9026.32	8548.111
Mar 24, 1994	129.81	145.5272	Apr 12, 2001	9378.99	9026.126
Mar 25, 1994	135.36	145.4753	Apr 16, 2001	9069.85	9337.572
Mar 28, 1994	142.14	145.4238	Apr 18, 2001	9448.61	8949.781
Mar 29, 1994	138.42	150.2015	Apr 19, 2001	9658.35	9586.089
Mar 30, 1994	136.5	153.0888	Apr 20, 2001	10131.1	9812.78
Mar 31, 1994	140.87	154.3684	Apr 24, 2001	10113.01	10445.54

Apr 01, 1994	150.28	155.0012	Apr 25, 2001	10890.07	10416.56
Apr 04, 1994	163.56	153.7283	Apr 26, 2001	12363.01	11311.13
Apr 05, 1994	175.01	153.0864	Apr 27, 2001	12367.36	12081.77
Apr 06, 1994	188.59	155.4605	Apr 30, 2001	12093.41	12076.09
Apr 07, 1994	186.11	192.3697			
Apr 08, 1994	200.35	215.4404			
Apr 11, 1994	204.92	209.6571			
Apr 12, 1994	203	196.1156			
Apr 13, 1994	207.59	195.8941			
Apr 14, 1994	221.04	200.4454			
Apr 18, 1994	214.72	202.7292			
Apr 19, 1994	212.82	196.6942			
Apr 20, 1994	206.4	194.6857			
Apr 21, 1994	194.28	189.6236			
Apr 22, 1994	184.73	182.4675			
Apr 26, 1994	168.67	172.0632			
Apr 27, 1994	159.77	191.3025			
Apr 28, 1994	158.26	196.8277			
Apr 29, 1994	150.97	188.6208			
	Actual	Forecast	Oct 17, 2008	26763.55	25427.06
Sep 01, 2008	40437.07	38389.72	Oct 20, 2008	26723.3	26343.76
Sep 02, 2008	40328.52	38839.92	Oct 21, 2008	25624.27	26421.01
Sep 03, 2008	39556.37	38803.27	Oct 22, 2008	25040.81	25650.33
Sep 04, 2008	39115.63	38487.8	Oct 23, 2008	24176.68	25257.51
Sep 05, 2008	40517.08	38282.09	Oct 24, 2008	24336.73	24705.85
Sep 08, 2008	40124.57	38893.06	Oct 27, 2008	24895.16	24811.84
Sep 09, 2008	39294.96	38772.79	Oct 28, 2008	26733.49	25243.81
Sep 10, 2008	37388.13	38436.3	Oct 30, 2008	27832.93	26902.85
Sep 11, 2008	37033.87	37417.75	Oct 31, 2008	27987.65	28106.08
Sep 12, 2008	35081.44	37193.23	Nov 03, 2008	29343.35	28484.14
Sep 15, 2008	33736.35	35611.26	Nov 04, 2008	27855.92	30028.92
Sep 16, 2008	32727.57	34234.62	Nov 05, 2008	27373.73	28371.5
Sep 17, 2008	32216.43	32895.4	Nov 06, 2008	26648.17	27954.66
Sep 18, 2008	36370.16	32010.04	Nov 07, 2008	26797.9	27330.86
Sep 19, 2008	36183.62	36245.48	Nov 10, 2008	25889.18	27474.28
Sep 22, 2008	35454.17	36027.71	Nov 11, 2008	25342.5	26662.02
Sep 23, 2008	35177.11	35322.7	Nov 12, 2008	25099.98	26241.62
Sep 24, 2008	36361.84	34957.27	Nov 13, 2008	25425.26	26061.76
Sep 25, 2008	36556.61	35994.14	Nov 14, 2008	24046.5	26300.94
Sep 26, 2008	36051.3	36193.98	Nov 17, 2008	23495.05	25129.53
Sep 29, 2008	34553	35891.33	Nov 18, 2008	21929.27	24725.14
Oct 03, 2008	31574.74	34386.61	Nov 19, 2008	21228.27	23749.99
Oct 06, 2008	31561.87	30962.69	Nov 20, 2008	21965.96	23423.24

Oct 07, 2008	30772.63	30952.3	Nov 21, 2008	24137.02	23784.71
Oct 08, 2008	30878.71	29857.5	Nov 25, 2008	24408.58	25291.26
Oct 09, 2008	28495.93	30032.15	Nov 26, 2008	25383.43	25270.05
Oct 10, 2008	28961.94	27340.6	Nov 27, 2008	25714.98	25957.98
Oct 13, 2008	30536.15	28041.37	Nov 28, 2008	24331.78	26260.33
Oct 14, 2008	29443.71	29845.26			
Oct 15, 2008	27600.71	28728.53			
Oct 16, 2008	25870.17	26875.07			