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Forecast of Borsa Istanbul Dividend Index (XTMTU) Trend by Using the Method of Artificial Neural Network

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Abstract
Use of artificial neural networks (ANNs) in the field of finance contributes to the solution of even the most complex problems by increasing the efficiency and the speed in decision making. Hopeful results have been obtained in the prediction of stock exchanges from the studies conducted by using artificial neural networks (ANNs) just like the other financial forecasts. In this study, we forecast the daily closing values between 03.01.2017 and 07.05.2017 by using the daily closing values of the Borsa Istanbul Dividend Index (XTMTU) betwen 02.03.2014 and 09.03.2017. Our main object in this research is to test the predictabiliy power of artificial neural networks (ANNs) by using the results obtained on the Borsa Istanbul Dividend Index (XTMTU). The results of our study indicate that the artificial neural networks determine the trend of the Borsa Istanbul Dividend Index (XTMTU) far better than many statistical and traditional methods.
Keywords: Artificial Neural Networks (ANNs), Multilayered Feedforward Network, Borsa Istanbul Dividend Index (XTMTU), financial analysis.

1.Introduction

Today, we see that computer technology is increasingly being used in the field of social sciences. One of the underlying reasons for this is that the amount of data used in social sciences has increased as never before like in other fields. Naturally, the amount of data saved and the conversion of these data into information has become more complicated as well as vital. The conversion of raw data first to the processed data and then to a meaningful decision has a critical importance for the researchers and for the enterprises in today's competitive environment.

Artificial intelligence is at the forefront of computer technologies that have recently been developed by imitating the functions of human intelligence. Although artificial intelligence technology has taken statistical and econometric techniques as a source of inspiration, it has a number of superior aspects as compared to these techniques. One of the major strengths of arttificial intelligence technology is its ability to model nonlinear relations very successfuly. Artificial intelligence technology, which has a capability of learning, provides many advantages to its users with regard to traditional statistical and econometrical methods such as its adaptation to different conditions, its dependence on less assumptions, its ability to process even incomplete, flawed, incorrect and mistaken data, its ability to model even the multivariate and complex relationships and its ability to work with qualitative as well as quantitative data. In this respect, it has become the best alternative for problems and analyzes where conventional methods can not produce solutions or produce weak and ineffective results.

A few different artificial intelligence technologies can be listed such as genetic algorithms, fuzzy logic and expert systems in addition to artificial neural networks when we consider the researches conducted until now. Although artificial neural networks that make up the subject of this study have been used for a long time in fields such as engineering and medicine as an artificial intelligence technology, their use in the field of social sciences has become widespread in the last 20-25 years. Economics and finance are two major areas of social sciences where this technology is frequently used today.

Financial analysis is a topic in which financial neural networks are used the most frequently in finance as well as in other artificial intelligence technologies. The types of financial analysis most commonly used by artificial neural networks are bankruptcy forecasting, loan and bond valuation, stock and portfolio selection, valuation of public offerings, profit forecasting, company takeovers and mergers, index forecasting, forecasting of financial crises, and performance measures. The decisions that are obtained from the financial analysis are critical for businesses and also for other users. The common feature of all these financial analyzes is that these financial analyzes contain a large number of variables, high ambiguity, extreme use of human labor, mutual and nonlinear relationships among variables, and lack of data. The mistakes that may occur as a result of these financial analyzes may result in financial losses in large quantities. On the contrary, successful results can be beneficial to the society by preventing large financial losses such as preventing financial crises and corporate bankruptcies.

The stock market index estimation, which constitutes the subject of this study, has recently attracted the attention of researchers. The stock market index is a detailed and statistical measurement of movements in a market or sector. The index, just like for the Borsa Istanbul Dividend Index (XTMTU), allows the performance measurement of a group of companies over a certain period of time. If price movements in a market are reflected in price indices, this is called stock exchange market.

In the rest of our work, in the first section, we will give brief information about the artificial neural networks and their structure as an artificial intelligence technology. Second section is the literature review in which we will review the studies that employed the artificial neural networks in the predicton of stock exchanges. The third section of the study will first give detailed information about the the aim, methodology and the sample of the empirical study. In the second part of this section, we will discuss findings obtained in the study and elaborate the evaluations. The study ends with the conclusion part.

2. Artificial Neural Networks as an Artificial Intelligence Technology

2.1. The Structure of Artificial Neural Networks

The basic element of artificial neural network is an artificial nerve cell called neuron. In fact, the artificial nerve cell (artificial neuron) is inspired by the nerve cell, the smallest element of the brain. Nerve cells come together for data processing activity and they form a group. The groups that they compose are called neural networks. Artificial neural network technology is an information processing technology arising from the imitation of nerve cells and neural networks in computer environment. It is an information technology that are run by being connected and parallel to each other and that each of them has its own processing ability and memory (Yildiz, 2009). Undoubtedly, the most important feature of artificial neural networks is its ability to learn even if it is limited as compared to human learning.

Artificial neural networks are a flexible computing method with the capacity to capture the connections between variables. The characteristics of an artificial neural network, such as the arrangement of the layers or cells, and their connection with each other, constitute the architecture or topology of the neural network. In order to design the most suitable artificial neural network for the analysis to be performed, the network topology, the number of network layers, the number of nodes in each layer, the activation function of the nodes, and finally the learning algorithm should be properly determined (Taghi, Niagi and Hoseinzade, 2013).

The topology of artificial neural networks are divided into feedforward networks and feedback networks: (Yildiz, 2009)

Feedforward Networks: In such networks, inputs are drawn either from the outside or from the previous nerve cell, and the outputs are fed into the next nerve cell or to outside. The most important feature of feedforward networks is that it is impossible for the nerve cell to communicate or to transmit data with another nerve cell in the previous or the same layer. Therefore, these networks do not have any dynamic properties but can be employed in linear and nonlinear analysis.

Feedback Networks: The most important feature that distinguishes feedback networks from feedforward networks is that in these types of networks, the outputs of the processing elements can be accepted as inputs to processing elements in the same layer or in the backward direction. In other words, feedback networks have some kind of feedback process. In this regard, feedback networks can model dynamic nonlinear systems, especially nonlinear differential equations. The most preferred type of artificial neural network in the time series is the three-layered feed forward models (Tosunoglu and Benli, 2012).

The most important factor about which topology should be selected for an analysis is the learning algorithm as they are developed depending on certain architecture. As a result of this process, the architecture to be used with the learning algorithm is also decided. For the artificial neural networks to function, it is necessary to determine the input values and output values, the structure of the network by benefitting from the past values and to train the network with a certain training algorithm to learn the network errors. Various techniques are used for network learning. These techniques can be classified as supervised and unsupervised learning. In supervised learning, the input and output vectors to the network are determined.The purpose here is to minimize the errors between the input and output vectors (Beale et al., 2014).

In unsupervised learning, there are no output vectors and input vectors are tried to be classified by considering the relationship between network input vectors. Multi-layered perception, which is a one of the supervised learning algorithms, is a layered and feedforward network trained by feedback. When feedback is processed, the network learns each input by comparing it with the target output vector and calculates the error function and processes it as back propagation or feedforward on the network (Yildiz, 2009).

Another factor affecting the architecture to be selected is the degree of complexity of the problem to be solved. The determinant factor in this point is the number of layers of the network. As the number of layers of the network increases, the ability of the network to solve complex and nonlinear problems also increases. The layers in the design of artificial neural networks can be categorized as follows (Tektas and Karatas, 2004).

Input Layer: The main task of the input layer is to transfer variables from the outer world to hidden layers.

Hidden Layer (s): The task of each hidden layer is to process the input variables so that they are passed to the output layer. The number of neurons in this layer is independent of the number of inputs and outputs.

Although, an increase in the number of neurons in the middle layers and in this layer leads to computational complexity and extends the computation time, it also helps artificial neural networks to produce solutions in more complex problems.

Output Layer: The operation of the output layer resembles the functioning of hidden layers. The process elements in this layer process the information from the intermediate layer and produce the required output for the production of the input set presented by the input layer. The output produced is sent to the outside world.

Multi-layered perception networks usually consist of an input, at least one hidden, and an output layer. Each secret layer operates with an activation function inside. The function used is usually sigmoid function. As the input changes in the sigmoid function, the output layer changes nonlinearly. Generalized feed forward networks provide the best solution to the problem by jumping over one or more layers. This is one of the most preferred methods.

3. Literature Review

Although there is a wealth of literature on artificial neural networks in developing countries, it is difficult to say the same for emerging countries. Some dynamics, such as the volatility that distinguishes developing countries from developed ones, the instability as a consequence of political developments, or the fact that financial markets are much shallower than those of developed countries, suggest that artificial neural networks need to be studied more before a decision is made about the predictive power of them in developing countries. In this context, some of the studies that have been conducted so far in the literature indicate that the predictive power of artificial neural networks in developed markets is higher than developing countries. On the other hand, some results support the opposite conclusions. For example, Harvey's (1995) study of more than 800 stocks in 20 countries in Latin America indicated that artificial neural networks give accurate results in developed countries, especially in stock estimates. On the other hand, Moreno and Olmeda (2007) argue that the predictability of stock markets in developed countries is higher than in emerging markets.

There are many studies using artificial neural networks in the stock market index estimation. Two of the earlieast of these studies belongs Kimoto et al. (1990) and Kamijo and Tanigawa (1990). These researchers tried to predict the TOPIX index of Japan, called the Tokyo Stock Exchange Prices Index, by analyzing correlations among many stock market factors and using artificial neural networks. Additionally, Trippi and DeSieno (1992) and Choi, Lee and Ree (1995) predicted the daily course of changes in the S&P (Standard & Poor's) 500 index.

Chen et al. (2003) compared the Generalized Method of Moments, Kalman Filter and Random Walk models with the prediction performance of artificial neural network techniques in their research on the direction of Taiwanese Stock Index. Researchers have concluded that the ability of artificial neural networks to predict is superior as compared to other methods.

Jasic and Wood (2004) made short-term estimates of the daily returns for the stock indices of S&P 500, DAX (German Stock Exchange), TOPIX and FTSE (Financial Times Stock Exchange) between 1965 and 1999. In doing so, they compared the predictive performances of artificial neural networks with the predictive performances of some of the chosen linear autoregressive models. They found that the buy and sell signals from artificial neural networks gave much more accurate results, which enabled investors to profit profoundly at a certain rate. Cao et al. (2005) compared linear models with artificial neural networks based on the Fama and French model in their study of the stock market in China. This study was taken as one of the studies in which artificial neural networks outperform linear models in terms of prediction power in the literature. Samanta and Bordoloi (2005) used artificial neural networks to predict the return of Indian stock market and obtained successful prediction results.

Artificial neural networks have taken place in the literature in recent years as a method that researchers increasingly use in finance. The number of studies using artificial neural networks and estimating various stock markets has increased markedly, including the studies conducted in 2000s on developing markets. Some of these studies belong to O'Connor and Madden (2006), Kiani and Kastens (2008), Faria et al. (2009), Feng and Cheng (2009), Liao and Wang (2010), Mehrara et al. (2010), Wang et al. (2012), Wei (2013), Patel et al. (2015) and Inthachot et al. (2016).

4. The Empirical Research

4.1. The Aim, Methodolgy and the Sample of the Empirical Research

Until recently, many traditional and statistical methods have been applied for the stock market index prediction. Along with artificial neural networks, the composition of many different learning algorithms has become one of the most frequently applied methods for stock market index prediction. The stock market index prediction is extremely complicated and highly volatile due to many factors such as political developments, market news and financial reports. It is often difficult to predict weekly or daily trends, even if technical data on the index is available on a daily basis (Ticknor, 2013). Therefore, the ability of the artificial neural network to learn from the nonlinear data trend by generalization provides great convenience to the researcher in the sense of stock market index estimation. In addition, artificial neural networks can better predict the relationships between inputs and outputs and provide much more accurate prediction results than conventional methods.

Artificial neural networks in the field of finance have been widely used by researchers since the beginning of 1990s. The high frequency of financial data, the high level of uncertainty, the complexity of modeling the relationships between variables makes the use of artificial neural networks increasingly preferred in financial analysis and forecasting. Artificial neural networks are technically used for regression and classification purposes.

In this study, a generalized-feed forward network (Rumelhart et al., 1986 ; Bambang et al., 2002) was used. All transactions were obtained using the sigmoid activation function in an ENCOG subset of JAVA programming language with an average of 10,000 training results. This function is of a quality that helps stop the network when it reaches the desired result. In the sigmoid function, as the input neurons change, the output layer also changes accordingly (Tektas and Karatas, 2004). Sigmoid function used in this study is ;

$$f(x) = \frac{1}{1 - e^{-x}}$$

It is a function often used for the activation of neurons in artificial neural networks.

In this study, daily closing values of Borsa Istanbul Dividend Index (XTMTU) between 02.03.2014 and 09.03.2017 have been used. Our main goal in this study is to test the success of artificial neural networks in measuring the predictive power of Borsa Istanbul Dividend Index (XTMTU) as an emerging market index by using the results of this research. The number of data used in the specified date range is 779. While 700 of these 779 were used as training set, 79 were used for validation. At the end of approximately 10.000 trainings, the best network was calculated as R2 = 0.8076722644712002 for validation and the network was estimated using this network.

In Figure 1, the structure of the network used is shown. As can be seen from the figure, the structure of our feed forward artificial neural network used in this study consists of an input layer, two hidden layers which consist of 15 hidden neurons in the first hidden layer and 10 hidden neurons in the second hidden layer and one output layer. While the number of input layers has been arranged as 30 (t, t-1, t-2 ... t-29), the training data set has been arranged as 700, and target error margin has been arranged as 0.001. The input layer is associated with the hidden layer that comes after it. The level of each relationship is related to the weights which indicates the strength of each relationship. The training algorithm used improves the learning ability of each neuron. After the related processes in the hidden layer are completed, the output layer is obtained by establishing a relationship with the output layer.

In this study, we used the quick propagation (QP) algorithm developed by Fahlman (1989) for network training. In this algorithm, which is based on full independence between weights, after a certain number of iterations, if no progress is made in the network, the initial weight values are changed and the iteration is started again. The QP method is based on renewing weights;

$$\frac{\partial E}{\partial w}$$

Calculates the value but the equation used to calculate Δw is ;

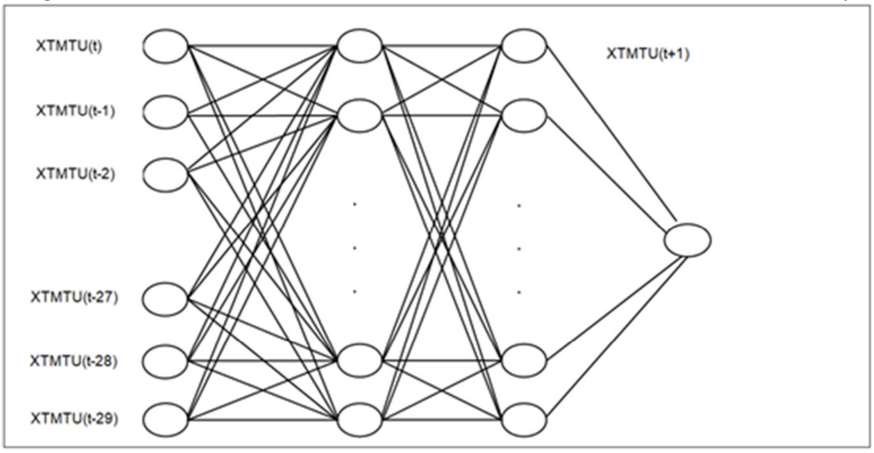
$$\Delta w(t) = \frac{S(t)}{S(t-1) - S(t)} \Delta w(t-1)$$

$$S(t) = \left(\frac{\partial E}{\partial w} \right)(t)$$

is expressed as a quadratic equation. It provides a faster and better solution than the back propagation algorithm that is one of training algorithms in solving many problems (Shanthi et al., 2009 ; Fahlman and Lebiere, 1989).

Artificial neural networks work with a very different model than conventional model building techniques. Neural networks constantly learn from the errors in the data, instead of modeling the problem. As the learning level increases in the network itself, it tries to minimize the error margin between the calculated output and the actual output by changing the weights. The predictive power of artificial neural networks stems from the fact that many mathematical relationships and processes are at the same time updating the weights connecting many neurons.

Figure 1: The Structure of the Feedforward Neural Network Used in the Study

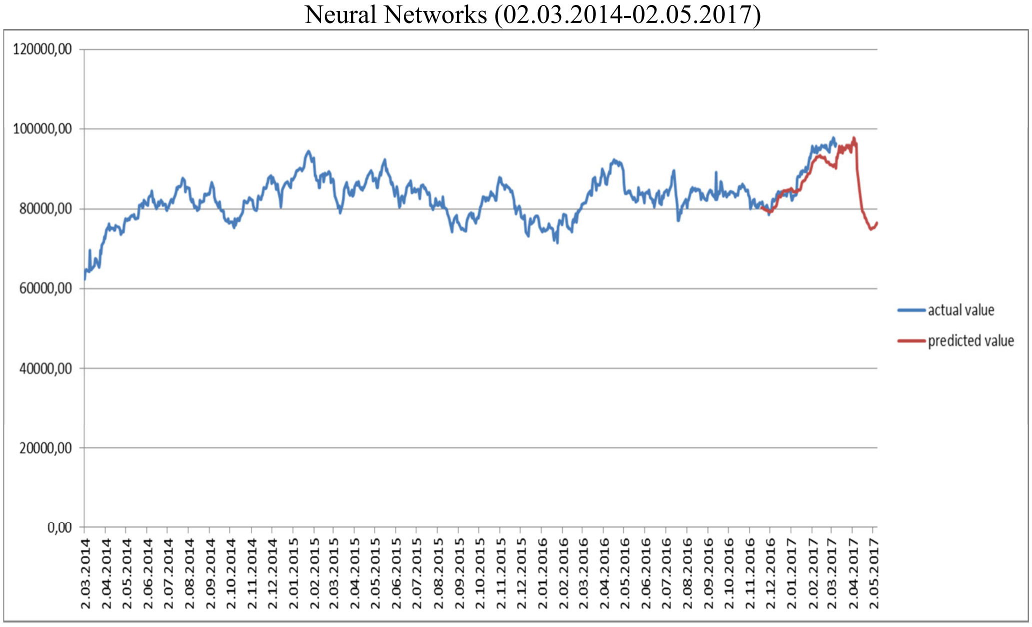


4.2. Findings and Evaluation

The results of the study obtained are shown in figure 2. A comparative graph of the actual values of the Borsa Istanbul Dividend Index (XTMTU) and predicted values of the artificial neural networks are presented in Figure 2. Many factors such as external stock markets, foreign economic developments, the index value of the previous day, the financial variables of firms and foreign exchange rates or interest rates can be influential on the course of the index values in the determined period.

According to Figure 2, the Borsa Istanbul Dividend Index (XTMTU) shows an upward trend between 02.03.2014 and 02.09.2014. From this date on, the index has followed a volatile course in the range of 80,000 and 100,000. Interestingly, the index began to rise from the point of 80.000 from our prediction date of 02.12.2016. According to Figure 2, it is observed that the predicted values represented by the red line and the actual values represented by the blue line are mostly close and parallel to each other between 02.12.2016 and 02.03.2017.

Figure 2: The Actual and the Predicted Values of Borsa Istanbul Dividend Index (XTMTU) with the Artificial Neural Networks (02.03.2014-02.05.2017)



By evaluating the actual and the predicted values shown in figure 3, one can make a detailed analysis on the trend of the Borsa Istanbul Dividend Index (XTMTU) between 03.01.2016 and 03.05.2017. As mentioned previously, the number of data that consists the actual values of the index in this study until 03.03.2017 is 779. The predicted values in the figure are composed of some test data and training data of the artificial neural networks from 02.03.2017 until 07.05.2017. It is striking that the red line, which represents the predicted values, show a sharp falling tendency starting approaximately from 02.04.2017 until the end of predicted period.

Both figures 2 and 3 indicate that the Borsa Istanbul Dividend Index (XTMTU) actually follows a fluctuating course in the determined time period. It is not possible to evaluate and comment the movements of the XTMTU index separately from the Borsa Istanbul 100 Index (BIST 100) because the companies included in the XTMTU are also included in the BIST 100 index. This volatile and fluctuating trend observed in the XTMTU can be said to be the consequence of some political and economic developments and the resulting instability occured in Turkey as a developing country.

Figure 3: The Actual and the Predicted Values of Borsa Istanbul Dividend Index (XTMTU) with the Artificial Neural Networks (03.01.2016-07.05.2017)

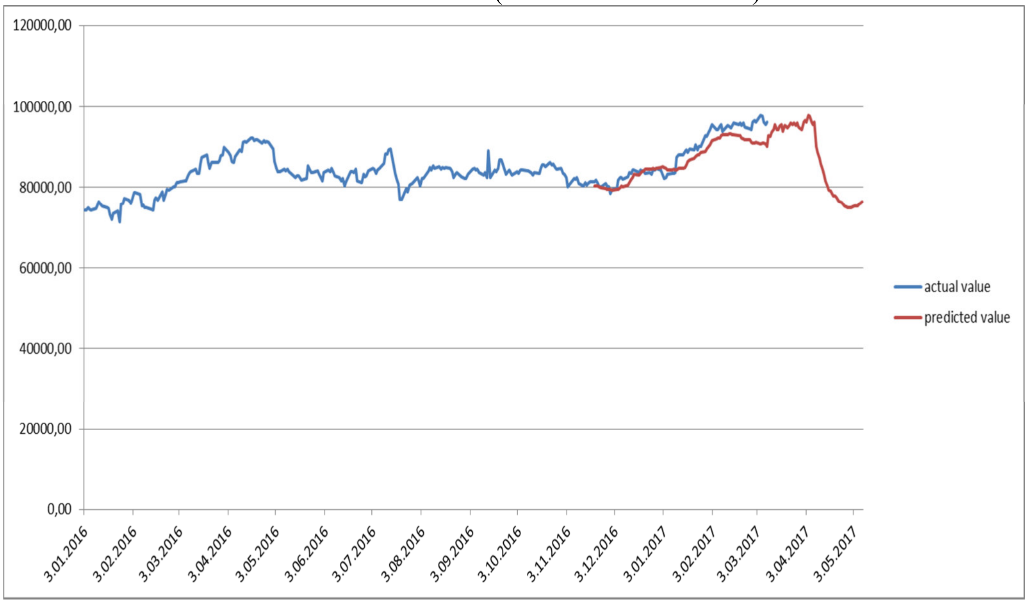
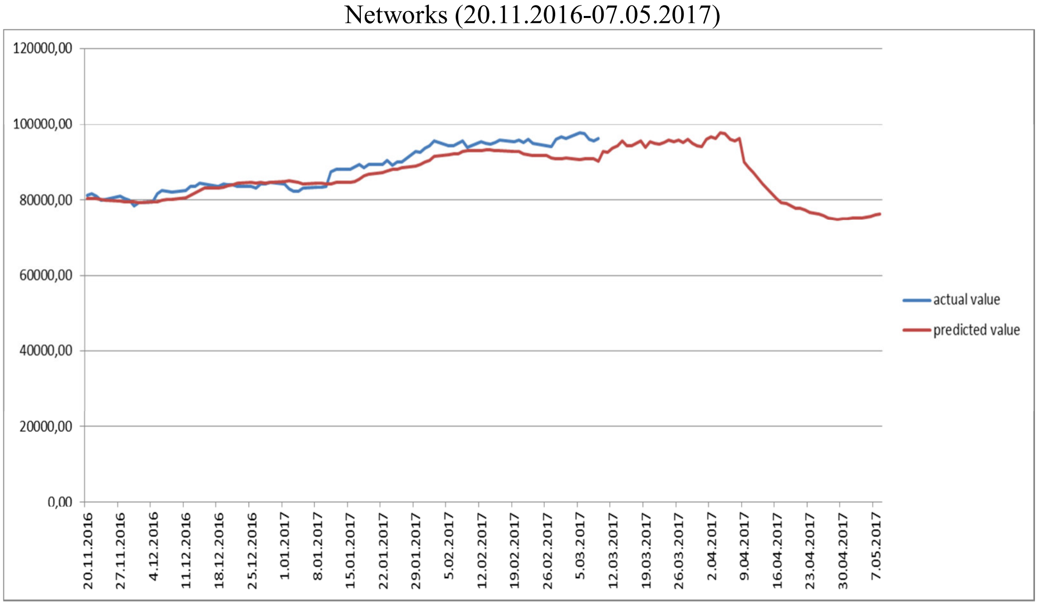


Figure 4: Future Prediction Values of Borsa Istanbul Dividend Index (XTMTU) with the Artificial Neural Networks (20.11.2016-07.05.2017)



In figure 4, the future forecast of XTMTU index values after 12.03.2017 are presented in more detail. As can be observed from figure 4, as of 12.03.2017, the index has followed a flat course followed by a significant decrease starting from 09.04.2017 until 30.04.2017. After this date, a minor increase in index values has been observed. Figure 4 also shows how close the actual values repesented by the blue line are to the predicted values reprsented by the red line between 20.11.2016 and 12.03.2017.

5.Conclusion

The 2008 global financial crisis, has had significant impacts on the companies as well as on the world stock markets worlwide. With the commencement of the crisis, stock exchanges have fell dramatically and investors have been hit hard. Subsequently, world economies entered into recession, and large fluctuations arose in the world stock markets, especially in the developing countries' stock markets. As globalization has already increased the volatility of stock exchanges, the recent global crisis has made it even harder to make financial estimates by increasing the volatility of the world stock markets. However, this has made the stock market index predictions more important than ever before.

Artificial neural networks are more frequently preferred in recent years as a prediction method because of the successful results obtained in high frequency series such as time series. In other words, even in situations where multidimensional, nonlinear relations exist and a definite mathematical model can not be established, they give effective results. Although, the nonlinear and nonstationary character makes the stock market index estimation difficult and complicated, as a result of studies made with artificial neural networks, promising results have been obtained in stock market index estimates as well as in other financial estimates.

In this research, the period between 03.01.2017 and 07.05.2017 was predicted with the aim of measuring the predictive power of the artificial neural networks in the financial forecasts using daily closing values between 02.03.2014 and 09.03.2017. As can be seen from the related figures in this study, the predicted values could be compared with the actual values for the period of 03.01.2017 and 09.03.2017. It has been determined that the predicted values and the actual values closely approximate each other in this comparative period. However, starting from 12.03.2017 until 07.05.2017, it has been predicted that the index tends to decline at a considerable rate. The actual and the predicted values of the Borsa Istanbul Dividend Index (XTMTU) indicates how volatile a stock index can be in a developing country due to unpredictable political and economical developments.

In Turkey, researchers generally prefer to predict Borsa Istanbul (BIST) 100 index when they conduct a research study with the aim of predicting an index by using artificial neural networks or other methods. In this sense, with this study, we aim to make a significant contribution to the existing literature by predicting the Borsa Istanbul Dividend Index (XTMTU) for the first time by using artificial neural networks. Prediction of XTMTU is as important as the prediction of other indices for the investors in terms of making effective transactions. In this regard, small investors as well as big investors can set their investment policies if the direction of the index can be predicted correctly. In this sense, the correct estimation of the index is important in terms of eliminating the uncertainty and establishing investor confidence.

Just as in other developing countries, financial analysis and predictions made by using artificial intelligence technology are very few in Turkey. The number of studies conducted by using artificial intelligence technologies in developing countries has only recently increased in the field of social sciences as compared to engineering and other fields. It is mainly because this technology is an area that requires expertise and equipment at a considerable level, and this expertise can only be developed after a gradual process. However, more and more researchers from the field of social sciences prefer to use them in their studies.

One major limitation of this study is that it is much more difficult to make financial predictions for developing countries like Turkey as many economic variables in developing countries can impact financial forecasts and the instability in the political arena can make financial forecasting difficult. In such a political and economic conjuncture, it may be regarded as normal that artificial neural networks or other methods are inadequate in estimates, especially in developing countries. Therefore, the specific situation of developing countries should be taken into consideration while estimating and interpreting the results.

Another important limitation of this study is that it is difficult for the researchers to make very long-term estimations by using daily values especially when the estimated time interval is long. In such a case, meaningless and distorted results can be obtained. Therefore, sometimes researchers may have difficulty in obtaining correct results when they make long-term forecasts on a day-to-day basis. Hence, hybrid methods using artificial neural network technologies and other artificial intelligence technologies such as genetic algorithms are seen as an important alternative between researchers in terms of overcoming this limitation and achieving highly accurate results.

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