A Feed-Forward Neural Network Approach to Istanbul Stock Exchange

[1]Mehmet YAVUZ, [2]Necati ÖZDEMIR

[1]Necmettin Erbakan University, Faculty of Science, Department of Mathematics-Computer Sciences, Meram, 42090, Konya, Turkey

[2] Balıkesir University Faculty of Art and Science, Department of Mathematics, Çağış Campus, 10145, Balıkesir, Turkey

[1]mehmetyavuz@konya.edu.tr, [2] nozdemir@balikesir.edu.tr

***Abstract*–In this study the trend estimation of the participation indices (PARTI) in the Istanbul Stock Exchange (BIST) using artificial neural network (ANN) theory. PARTI can be regarded as the Participation 50 Index (KAT50) and the Participation 30 Index (KATLM). Since KAT50 has only been calculated since 9th July 2014, there are only a few studies on this index. On the other hand, PARTI indices are growing more and more important in global economies, especially in Turkey, England, etc. Therefore, in this study, firstly, we have used ANN method, using 1410 daily closing values of KATLM, between 1st August 2012 and 30th June 2016. For the KAT50 index, we used 720 daily closing values between 9th July 2014 and 29th July 2016. We created a feed-forward back-propagation neural network model in order to predict the trends of these indices and we applied the previously mentioned daily closing values of these participation indices to this model. The results obtained using the ANN method are compared in the figures and tables. It can be concluded that the results of this study are very helpful for individual and institutional investors' investment decisions within global economies.**

***Keywords*: BIST, participation index, artificial neural network, trend prediction.**

I. INTRODUCTION

People pay attention to financial developments on a day-to-day basis. During the last few decades especially, new algorithms and methods have been generated relating to financial modelling and simulation. Artificial neural networks (ANNs) are extensively used in the solution of real-life problems, especially in financial areas. For example, this technique is used to evaluate the performance of financial shares, to detect exchange rate directions, to evaluate customer demands, to solve portfolio-selection problems, to plan workforces, to estimate stocks and indices, to forecast the bankruptcy of companies, to predict financial crises, to determine manipulative transactions, to price options, for portfolio optimization, etc.

Estimation of financial indicators (indices/prices) is a complex and quite difficult issue because they depend on many factors such as political events, financial ratios and economic variables. The psychological make-up or decision-making styles of investors or experts are also major reasons for this difficulty [1]. In addition, many economic factors influence indices. Political stalemates in the country, investors' tendencies and expectations, economic productivity, the status of foreign investments on the index, preferences of corporate investors, etc. all have a very important effect on stock market prices. There are many approaches and techniques for estimating index values, such as time series analysis techniques, genetic algorithms and multiple regression models. However, there is a notable lack of studies on the estimation of indices in Turkey. Therefore, the aim in this study is to demonstrate the predictability of the KATLM and KAT50 indices using a special feed-forward neural network model.

II. LITERATURE REVIEW

Many studies have been undertaken in the last quarter of a century on stock index prediction using neural networks. Yao and Poah [2] used a back-propagation neural network method to make forecasts for the Kuala Lumpur Stock Exchange (KLSE). This study is one of the first studies on index prediction using neural networks. The findings showed that useful predictions can be made without the use of extensive knowledge and big market data.

Avcı [3] examined the power of neural networks for predicting ISE traded stock returns, and showed that the neural network models could beat the buy-and-hold strategy for most of the periods under investigation. Dixit et al. [4] applied artificial neural networks to the India VIX between January 2010 and January 2013. The models they developed performed better than other trained models in terms of the overall estimation percentage. Monfared and Enke [5] considered a hybrid GJR-GARCH model for volatility forecasting. They studied four different economic cycles in order to train and test their neural network model. Their results showed that the hybrid model achieved the prediction of volatility and the model was a good candidate for using the CVaR measure in portfolio risk management. Yavuz et al. [6] used the monthly average returns of 140 stocks contained in the industrial index of ISE for the year 2010, aiming at risk-return forecasting and portfolio optimization. They obtained an error rate for the ANN's return prediction of approximately 1%, and the error in the risk estimate was observed to be less than 0.5%. Sıddıqui and Abdullah [7]

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studied the CNX Nifty 500 Index, using the S&P 500, Euro Stoxx 50, Shanghai Composite and Nikkei 225 indices as independent variables. They also used daily closing values data for the index from January 2004 to December 2013.

Sakarya et al. [8] examined the predictability of trends in the BIST-100 Index. They used a multilayer perceptron ANN model and successfully predicted daily and weekly returns of the index during the global crisis period (July 2007 - December 2009). The results they obtained show that ANN can predict the value of the BIST-100 Index correctly for the next day and the next week, with a margin of error of less than 5%, even for unknown samples. Telli and Coşkun [9] forecasted the BIST-100 Index using an ANN, giving consideration to the economic calendar. Their predictions achieved a mean-square error of 0.025 and an R^2 value of 0.88. Moghaddam et al. [10] investigated the ability of ANN to forecast the daily NASDAQ stock exchange rate. They assessed several feedforward ANNs that were trained by the back-propagation algorithm and assessed the methodology with respect to short-term historical stock prices

III. Participation Indices Using Artificial Neural Networks

Based on an analogy with biological neural networks, ANNs are intelligent computing systems which assist in the automation of real-world applications [11]. In this part of the study, the aim is to estimate the status of the KATLM-KAT50 indices using an ANN. For this purpose, feed-forward back-propagation networks are used. For training, a set of data obtained over 33 months (1st August 2012 - 30th April 2015) was used for KATLM, and a set obtained over 16 months (9th July 2014 - 30th October 2015) was used for KAT50. These data were obtained from the Turkish Central Bank database, and were composed of a number of variables, namely, participating banks' balances, participating banks' foreign assets, participating banks' loans, participating banks' collected funds, gold prices, exchange rates, money supply and consumer price index (CPI). These economic indicators are the most important factors influencing the participation index [8].

The test data set extends over 14 months (1st May 2015 – 30th June 2016) for KATLM, and eight months (1st November 2015 – 30th June 2016) for KAT50. The topology of the network is composed of one input layer, three hidden layers and one output layer for both KATLM and KAT50. The numbers of neurons in each layer are eight, seven, six, five and one respectively, as shown in Figure-1.

A number of different combinations of hidden layers and number of neurons have been used to achieve best performance in the feed-forward back-propagation network. In addition to this, a number of different learning rates and momentum coefficients have been used in order to optimize our design. In order to choose of the optimum values used in the ANN model, we have criticized about the values and we have shown our optimization strategy in Table-1.

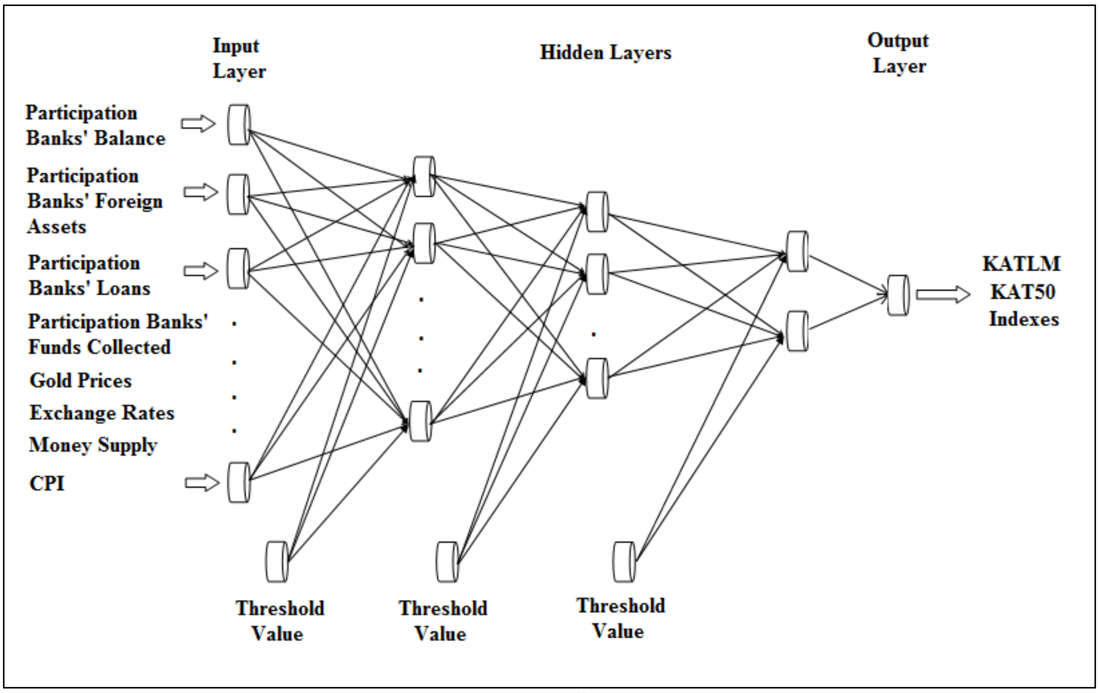

Figure 1. MLP network topology for the participation indices

TABLE1. DETERMINING THE OPTIMUM VALUES FOR THE FOUNDED ANN MODEL

Number of Hidden Layers	Momentum Coefficient	Learning Rate	Mean Square Errors	
			KATLM	KAT50
2	0.01	0.02	0.0958	0.0314
2	0.02	0.03	0.0892	0.0490
3	0.03	0.04	0.0413	0.0359
3	**0.01**	**0.05**	**0.0213**	**0.0243**
4	0.02	0.02	0.0331	0.0382
4	0.03	0.03	0.0283	0.0369
5	0.01	0.04	0.0472	0.0423
5	0.02	0.05	0.0443	0.0361

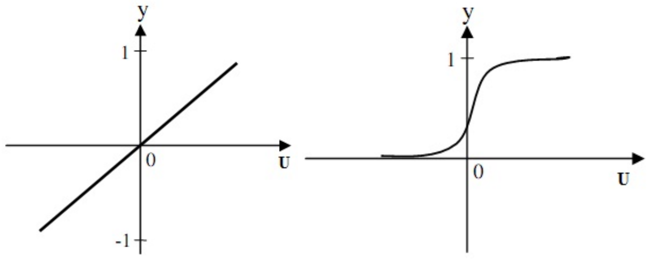

Figure 2 (a): Purelin function (b): Tangent sigmoid function

For the input layer neurons, we have used the purelin function as the activation function. For the other neurons in each layer we have used the tangent sigmoid function. The structures of the purelin function and the tangent sigmoid function are presented in Figure-2(a) and Figure-2(b).

Two different types of purelin function can be defined, i.e.,

$$U=\sum_{i=1}^{n} x_i w_i+\theta \text{ or } U=\sum_{i=1}^{n} x_i w_i-\theta \text{ and } Y=f(U)=AU,$$

where A is a constant, θ is the threshold value and U is the sum of the net input. The tangent sigmoid function can be represented as $y=f(U)=\dfrac{1}{1+e^{-U}}=\dfrac{1}{2}\left[\tanh\left(\dfrac{U}{2}\right)-1\right]$.

The training of the ANN was performed using Microsoft Visual Studio C#.NET 2013. The standardized data, the structure of the ANNs used and the mean-square errors (MSE) are presented for the KATLM and KAT50 predictions in Figure-3 and Figure-4.

The pseudocode for the ANN is as follows in figure 5 [8].

IV. TEST RESULTS AND DISCUSSION

In this study, the KATLM index values between May 2015 and June 2016, and the KAT50 index values between November 2015 and June 2016 are used as the test values. Using the values of eight factors (participating banks' balances, participating banks' foreign assets, participating banks' loans, participating banks' collected funds, gold prices, exchange rates, money supply and CPI) measured at the end of the month, the KATLM and KAT50 indices are predicted using an ANN model. The test results are given in Table-2 and Table-3 for KATLM and KAT50, respectively.

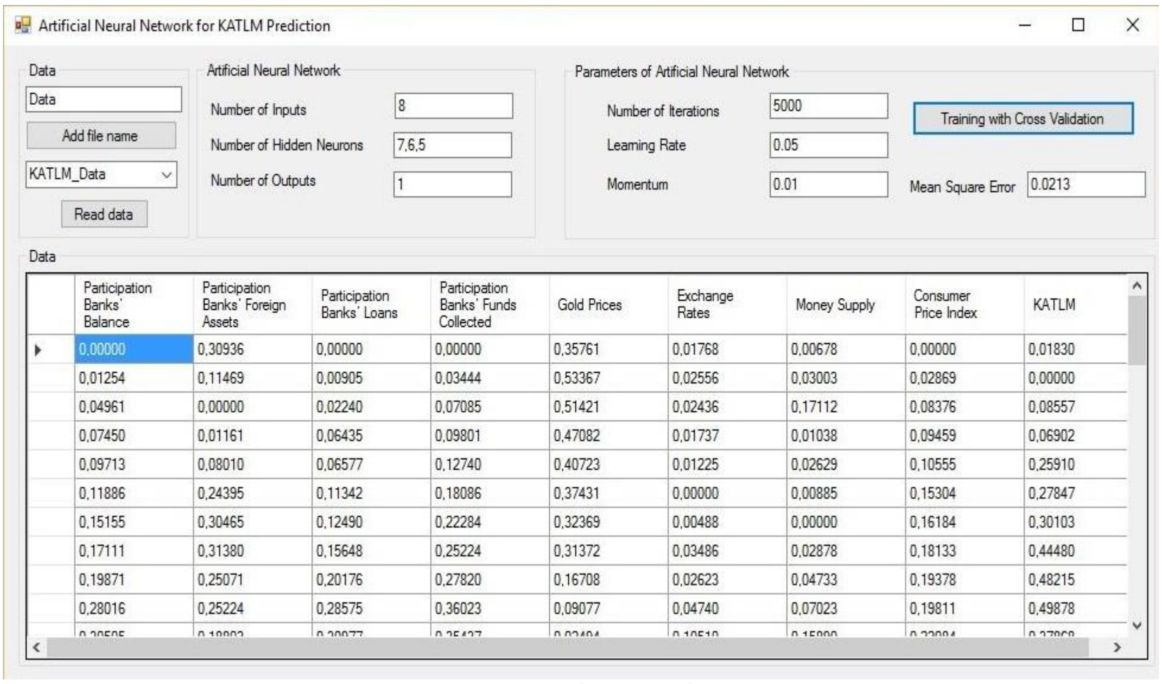

Figure-3. Structure of ANN used for KATLM

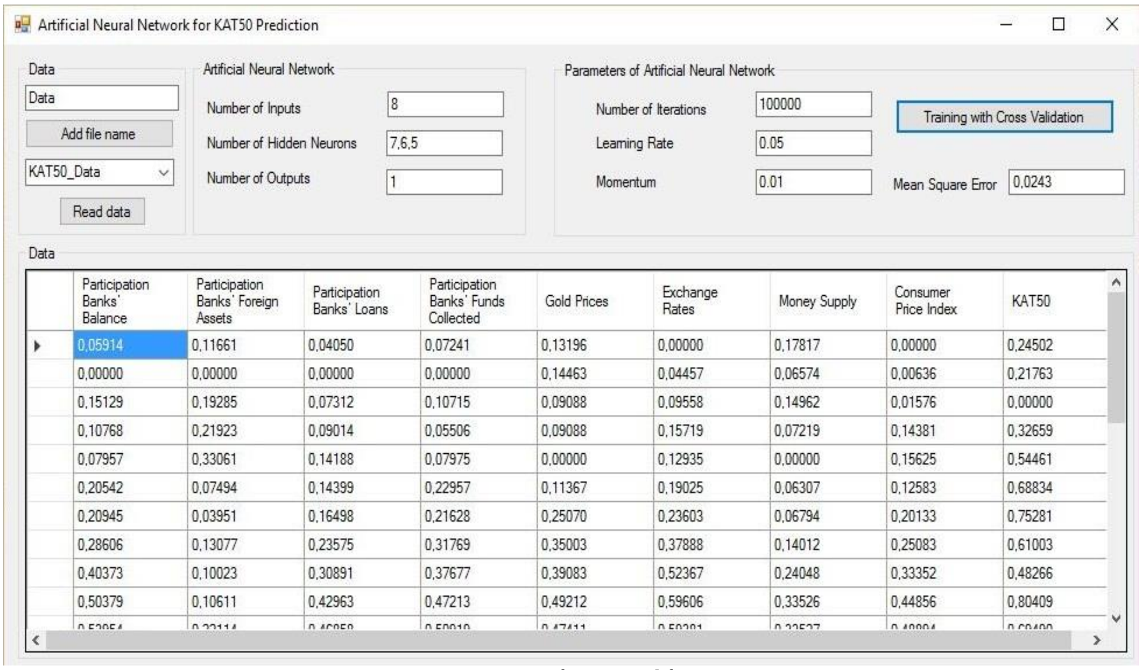

Figure 4. Structure of ANN used for KAT50

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Define the input matrix as (P0) and calculate its transpose as (P)
Define the output matrix as (T0) and calculate its transpose as (T)
Determine the number of neurons of the input layer as (S0)
Determine the number of neurons of the hidden layers as (S1, S2, S3)
Determine the number of neurons of the output layer as (S4)
Construct the network topology, using the initialized weights between -1 and 1
start training by using the code given below:
[Pn, minP, maxP, tn, minT, maxT] = premnmx (P,T);
[Net = newff(minmax(P), [S0, S1, S2, S3, S4], 'traingd'];
net.trainParam.epochs = …;    net.trainParam.goal = …;        net.trainParam.show = …;
net.trainParam.mc = …;                  net.trainParam.lr = …;   net.trainParam.lr_inc = …;
net = train(net,P,T);              save training result.
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Figure 5. The pseudocode for the ANN

The KATLM prediction was performed for 1th August 2012 and 30th June 2016. The KAT50 prediction was performed for 9th July 2014 and 30th June 2016. Because the KAT50 only began on 9th July 2014, there has been almost no work done in this area. Therefore, our study fills an important gap in the literature. The errors between the predicted and observed values are given in columns (C) and (F) in Table-2 and Table-3. When these error values are examined, the overall error rate for a long-term period is lower than 2.5%. These results show that the trained ANN has the ability to make accurate predictions for samples that were not used in the training phase. The prediction errors for the KATLM index values ranged between 0.00247 and 0.03765, and the prediction errors for the KAT50 index values ranged between 0.018494 and 0.028605. The overall mean prediction error for the KATLM index is calculated as 0.02130 (2.13%) and the mean prediction error for the KAT50 index is calculated as 0.02430 (2.43%). In general, we can say that ANNs are able to estimate this aspect of the KATLM-KAT50 indices.

Predictive models such as genetic algorithm, artificial neural network, ant colony and Markov chain, etc. are able to predict the economic stochastic processes with very small error rate when the conditions in the real market are normal. However, in the case of sudden positive / negative political or economic developments, these error rates increase because such prediction models do not predict these sudden fluctuations.

In this section, we will compare our results with those of some of the studies in the literature. Although there have been no studies in the literature about prediction of the participation index to date, there are some findings about index trend estimation. Among these, Kara et al. [12] estimated the direction of the ISE National 100 Index with ANN and support vector machine (SVM) techniques, using daily data between 1997 and 2007. In the study, 10 technical analysis indicators were used as input data and the estimation performance of the artificial neural network method was 75.74% higher than for the other method. Ibrahim et al. [13] modelled a thermal model of ten datasets obtained from the UCI data warehouse using back-propagation (BP) and Levenberg-Marquardt (LM) training algorithms. They compared the algorithms with respect to mean square error and classification accuracy. The results they obtained showed that the BP algorithm (89.2%) had accuracy better than the LM algorithm (86.7%).

Guresen et al. [14] developed a multilayer perceptron (MLP) model and used it to forecast the future movements of the NASDAQ index. The MLP model correctly forecasted the first movement as down. The realized value (1,747.17) differed only slightly (0.54%) from the forecasted value (1,737.70). In another study, Qui et al. [15] predicted the return of the Japanese Nikkei 225 Index with a back-propagation neural network (BPNN) model. They demonstrated the best BPNN model, which had effective performance with an MSE value of 0.0044. In a similar study, Masoud [16] predicted the movements of stock prices exactly in the daily Libyan Stock Market (LSM). In this study, the experimental statistical results showed that the ANN model accurately predicted the direction of movement with an average prediction rate of 91% for the best case of the data analysis.

On the other hand, regarding different applications of the proposed methods, in [17] the authors used a Markov chain model and two neural networks to predict the profits contributed by a customer under various purchasing behaviours. The proposed framework was demonstrated with historical customer transactions from a car repair and maintenance company in Taiwan. They obtained prediction accuracies for the two neural networks of about 94% in the training sample and 92% in the testing sample. In [18], the authors modelled the management of the water network using a single-layer extreme learning machine (ELM). The developed ELM model gave results with coefficients of determination ranging from 0.67 to 0.82. This was achieved with a maximum of 50 neurons in the network hidden layer and a triangular basis function.

V. Concluding Remarks

In recent years, the participation index (PARTI) has become a very well-known and commonly used index in BIST (Istanbul Stock Exchange).

Turkish people especially pay increasing attention to participation banking. Therefore, it is very important to be aware of PARTI. In this study, the predictabilities of the KATLM-KAT50 participation indices during the period 1st August 2012 – 30th June 2016 were investigated using artificial neural network model. A new ANN algorithm for the estimation of PARTI is presented, and using this algorithm we have made predictions for unknown samples of PARTI. In addition, our model has successfully predicted the direction of PARTI with low errors, between 0.00247 and 0.03765.

Table 2: Comparing the KATLM index values and ANN findings

Years	**Months**	**(A) KATLM Index**	**(B) Predicted value of KATLM Index with ANN**	**(C=(A-B)/A) Error**
2015	May	80,301.20	82,356	0.02559
	June	79,723.57	81,356	0.02048
	July	76,854.13	78,104	0.01626
	August	75,052.57	75,735	0.00909
	September	75,959.92	77,906	0.02562
	October	80,410.29	81,309	0.01118
	November	78,076.05	77,883	0.00247
	December	73,269.27	74,595	0.01809
2016	January	74,336.86	72,993	0.01808
	February	77,677.86	74,912	0.03561
	March	85,325.34	87,964	0.03092
	April	85,375.79	83,124	0.02638
	May	79,581.22	81,237	0.02081
	June	76,685.81	79,573	0.03765
Mean Error				**0.02130**

Table-3: Comparing the KAT50 index values and ANN findings

Years	**Months**	**(D) KAT50 Index**	**(E) Predicted value of KAT50 Index with ANN**	**(F=(D-E)/D) Error**
2015	November	78,309.30	80,387	0.026532
	December	73,589.98	75,695	0.028605
2016	January	74,548.09	76,621	0.027806
	February	77,716.11	75,632	0.026817
	March	85,336.17	87,320	0.023247
	April	85,379.77	87,061	0.019691
	May	79,738.32	81,213	0.018494
	June	76,853.57	78,637	0.023206
Mean Error				**0.02430**

The results of this study show that ANN can successfully predict the direction of the index values with an accuracy margin of error of less than 2.5%, even for unknown samples, thus achieving results which are very close to the real market results. This outcome is very important for investors, especially portfolio managers considering investments in these indices.

The results obtained with ANN are likely to be helpful with regard to individual and institutional investors' investment decisions and their portfolio preferences.

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