The Role of Technical Indicators in the Intraday Prediction of Stock Markets: Artificial Neural Network Models for Borsa Istanbul

Andaç Batur Çolak[1,*], Ayben Koy[2]

[1]Istanbul Commerce University, Information Technologies Application and Research Center, Istanbul, 34445 Türkiye

[2]Istanbul Commerce University, Faculty of Business, Finance and Banking Department, Istanbul, 34445 Türkiye

Abstract

In this study, two simulation models have been developed to predict the main stock price index of Borsa Istanbul with an artificial intelligence approach. To analyze the role of technical indicators in intraday predicting of stock markets, two different artificial neural network models have been developed in which different parameters are defined in the input layers. In the first model, 5 input parameters have been defined as open price, highest price, lowest price, and two different moving averages, 3 more parameters added as The Relative Strength Index, The Moving Average Convergence Divergence and the moving average of this. The Borsa Istanbul value has been predicted. 70% of the data used in multi-layer network models developed with a total of 97 data sets have been used for training the model, 20% for validation and 10% for testing. The results show that both neural network models can predict Borsa Istanbul values with very low error rates. However, it is seen that the prediction performance of the first model, which has been developed by defining fewer input data, is higher than the second model. In addition, the results obtained support that the predictions made with intraday data are stronger between 13:00 and 16:30.

Keywords: BIST100, artificial intelligence, simulation, technical indicators, Stock Markets

*Corresponding author. Tel: +90 533 201 75 39, Fax: +90 216 489 02 69

E-mail addresses: (abcolak@ticaret.edu.tr) (A.B. Çolak), akoy@ticaret.edu.tr (A. Koy)

1. Introduction

Financial markets form a large ecosystem where technological developments are followed in the form of speed and new products. Artificial intelligence, deep learning, algorithms, blockchain are among the prominent topics in this ecosystem. Recently, algorithms and technologies using artificial intelligence perform a significant part of the trade in financial markets. In the markets where information is rapidly reflected in the price, computers trade, or professionals often get support from those computers and new technologies.

In financial markets, where the importance of speed and technology has increased, many methods have been developed to buy or sell the right asset at the right time. Technical analysis is taking an increasing place in the trading decisions of both professionals and robots. Although the importance of fundamental analysis in the investment decision for an asset is generally accepted, the rapid exchange of information in national and international financial markets makes it important to measure the contribution of technical analysis to success.

The random walk hypothesis underlying financial theory states that stock prices cannot be predicted [1]. It says that the changes in stock prices have the same distribution and are independent of each other. In today's technology, while the information coming to the market is reflected in the price quickly, can those who benefit from the advantages of the technology, by estimating the asset prices in this random walk process, obtain an abnormal return? Do short-term abnormal returns of investors who use technology and forecast asset prices dismiss theories that the market is efficient in the long run [2, 3]? While the theoretical discussions continue, the methods used in the finance sector for estimating asset prices are also developing. In this context, the search for gaining high returns in emerging markets by forecasting prices is still up-to-date in line with the risks posed by emerging markets compared to developed markets. This study, which predicts intraday prices with artificial intelligence models using technical indicators in an emerging market, Borsa İstanbul, also provides evidence for related searches.

Prior works show that ANN models generally perform better than other models. However, the number of studies analyzing the intraday price movements with ANN models is quite limited for emerging markets. Especially for Borsa Istanbul, where is an emerging stock market with a share of foreign investors that has been over 50% for many years, the little literature is very weak. One study that predicts the intraday price movements with neural network models belongs to Gunduz et al [4]. In their Convolutional Neural Network (CNN), which is a deep learning methodology, taking Borsa İstanbul 100 stocks as a sample, the hourly movements of 100 stocks predicted using technical indicators temporal features. The leading algorithm with the best Macro-Averaged (MA) F-Measure metric scores in 54 of 100 stocks is CNN-Corr model with the reordered features according to clustered feature correlation. In the nest study using deep learning, Raşo and Demirci [5] predict BIST 30 Index for a period of 27 months. In their successful technical analyzed based model they use many indicators like The Relative Strength Index (RSI), Bollinger bands, Stochastic Oscillator and The Moving Average Convergence Divergence (MACD).

In one of the first studies using ANN for Borsa İstanbul, Egeli et al.[6] examined the day of the week effect. The findings obtained in the study using daily observations as index value, TL/USD exchange rate, overnight interest rate, and 5 dummy variables for each day, revealed that ANN models perform better than moving averages (MA). In another study using daily data between 29th July and 15th November of 2015 for BIST 100, Telli and Coskun [7] make several predictions for BIST100 including variables as exchange rates (USDTRY, EURUSD, USDJPY), stock indices of developed markets (DAX, Dow Jones, FTSE,…), and an economic calendar with news days are 1, others are 0 related with Turkey. It is one of the main results that the economic calendar is a good explanatory variable to predict BIST100. Aksoy [8] used different models to predict the stock price for manufacturing industry companies in Borsa Istanbul. According to the results, general classification accuracy was achieved 98.05% for Artificial Neural Networks, 96.10% for Classification and Regression Tree, and 92.20% K-Nearest Neighbor Algorithm. “Net Profit Margin”, “Price/Earning”, “Profit Per Share”, “CDS Premium (3-month average)”, “Consumer Confidence Index” were found as important variables that divided the data into two in the creation of the Classification and Regression Tree (CART) analysis.

As analysis methods evolved, hybrid models that use different methods such as artificial intelligence and time series analysis together developed. One of the studies using hybrid models composed of time series and other methodologies together is Bildirici and Ersin’s [9]. In the study which provides evidence that ANN models strengthen predictions, the volatility of BIST100 is analyzed with methodologies combining Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models with ANN models for a daily data set for 23.10.1987-22.02.2008 period. Their results indicate that the conditional variance models augmented with artificial neural networks capture the volatility more efficiently. Different hybrid models have been used to predict stock market indices. Using monthly data, Boyacıoğlu and Avci [10] predict BIST100 with the Adaptive Network-Based Fuzzy Inference System (ANFIS). In the study using macroeconomic variables, DJI, DAX, BOVESPA Indices, and monthly returns of BIST100, the index is forecasted with an accuracy rate of 98.3%. In the study Göçken et al. [11] using technical indicators as closing price, moving averages, and momentum price to predict BIST100 with daily data, hybrid ANN models were used. Above their models based on a heuristic optimization methodology (Harmony Search (HS) or GA) the HS-ANN model is found significantly better than others. ANN models are also used to create the most successful portfolio in stock markets. Ozcalici and Bumin [12] find selecting the stocks with the assistance of artificial neural networks made it possible to obtain excess returns over the market in Borsa Istanbul.

Due to the limited number of studies on Borsa İstanbul, it is also important to provide information about the findings of similar studies for the other markets. Adebiyi et al. [13] study predicting Dell Inc stock price with the data for 23 years, they find ANN models more successful compared to autoregressive integrated moving average (ARIMA) models. In a stock-based study applied to Apple, IBM, and Dell, Hassan et al. [14] implement a fusion model by combining the Hidden Markov Model (HMM), Artificial Neural Networks (ANN), and Genetic Algorithms (GA). Their findings indicate that the performance of the fusion tool is better than that of the single HMM. Moreover, the forecasting ability is good as ARIMA model. In another study [15] implementing an experimental case study on stocks in S&P 500, reactions to anomalies are predicted using a feed-forward deep learning network. The study recommended to use multiple layers as long as the model does not overfit the data, as the results for multiple hidden layers tend to be superior.

Using an extensive data set consist of 15 technical analysis variables as closing price, volume, moving averages, and 11 fundamental analysis variables as brent oil price, consumer confidence index and, automobile sales, Oliveria et al. [16] predict the direction of stock prices trading in Brazil Bolsa Balcao (BM&FBOVESPA). In the different window sizes they designed, the best performance belongs to the window size of three in their ANN model. Including 24 technical indicators as MACD and RSI as input variables, Chang et al. [17] use evolving partially connected neural networks (EPCNNs) to predict Citigroup and Motors Liquidation Company stocks in SP500 in three different experiments. According to their results, the prediction accuracy for training data reaches at least 94%, and the percentage prediction accuracy for testing reaches at least 97%. In the second experiment that was done in the same study, the results indicate that the percentage prediction accuracy of the model with lower numbers of neurons and lower numbers of layers tested for Citigroup is higher. In the last experiment, some advantages are found for the prediction power of EPCNN while compared with other models for TSE (Taiwan Stock Exchange) index. Six stock market indexes are predicted by a quantum artificial neural network [18]. The proposed algorithm that double chains quantum genetic algorithm is employed to tune the learning rates is found efficient and successful.

The role of technical indicators are studied with deep learning for the Chines stock market [19]. The convolutional neural network (CNN) model predicted using 27 technical indicators and 5 original price series could obtain 70% forecasting accuracy on average. Including technical indicators as MACD and EMA, Liu et al [20] predicted stock market indexes based on ISSA-BP neural network models. Their model predicts successfully in the short term. Chandar [21] used a convolutional neural network for stock trading using technical indicators on NASDAQ and NYSE data. Their model resulted in high prediction accuracy. Performance indicators such as accuracy and F1 score are calculated and compared to prove the effectiveness of the proposed stock trading model.

There are two main features that make this work stand out. First of all, a remarkable part of the financial professionals make investment decisions according to the price movements in one day in the financial markets, and although artificial intelligence is used to a great extent in this decision phase, however, there is not enough literature examining the intraday price movements with ANN models for emerging markets. On the other hand, studies that include indicators used in technical analysis in ANN predictions are limited. In these limited number of studies, generally, there is no preliminary research on the selection of indicators. This study, in which the most frequently used indicators are determined and their contribution to the predictive power is analyzed as a result of interviews with the users of technical analysis and indicators, is applied to the intraday data of the stock market and offers important facts to the literature and professionals.

2. Methodology

2.1. Data Collection

All variables used in the study are obtained from the Matriks IQ trading platform and shown in Table 1. Matriks IQ is a database of Matriks Bilgi Dağıtım A.Ş. which is a fintech company established in 2003 and whose stocks went public in 2021. Technical indicators downloaded from the Matriks IQ are ready to analyze because the trading platform calculates them.

Finance professionals use a large number of different tools for technical analysis. Before starting modeling, 21 professionals were interviewed to determine which technical analysis tools are used more when trading in the markets. As a result of these negotiations, it was concluded that The Relative Strength Index (RSI) and The Moving Average Convergence Divergence (MACD) values are mostly used in addition to the past prices and averages. MOST, Fibonacci, Ichimoku and Bollinger Bands are the other indicators mostly used by the professionals that we have learned from their responses. The other variables used to predict the BIST100 closing value in the study are the opening price (OP), highest price (HP), lowest price (LP), and moving averages for 15 minutes (MOV15) and 60 minutes (MOV60).

RSI is a momentum indicator used in technical analysis. It measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset. RSI takes a value from 0 to 100. Overbought (over 70), and oversold (below 30) zones signal that the price will go in the opposite direction.

MACD is a trend-following momentum indicator that shows the relationship between two moving averages of a security's price. The MACD is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. It is an oscillating indicator that varies over time within a band. The last variable TRIGGER is a moving average plotted on the MACD indicator that is used to generate buy and sell signals for a stock.

The period under consideration is selected as the last day of September 2020, when the high price movements caused by the covid19 pandemic relatively decreased. In the dataset, in which 5-minute daily observations are used, there are 97 observations for each variable.

2.2. ANN model development

Two different ANN models have been developed in order to analyze the role of technical indicators in the intraday forecast of the stock markets. In the developed ANN models, the feed-forward (FF) back-propagation (BP) multi-layer perceptron (MLP) model, which is frequently preferred in the literature, is used [22]. MLP network models have one input layer where data is entered, at least one hidden layer and one output layer where predictive values are obtained. Each layer is connected to the next and between the layers there is a computational element called a neuron [23]. There is no fixed model or correlation used to optimize the number of neurons to be used in ANN models [24].

In order to analyze the role of technical indicators in predicting the stock markets during the day, two different ANN models have been developed in which different parameters are defined as input parameters at the input layer, and the effect of input parameters has been examined in detail by analyzing the prediction performance. In the first ANN model developed for this purpose and named as Model 1; 5 input parameters, OP, HP, LP, MOV60 and MOV15, have been defined and BIST100 value has been predicted at the output layer. In the second ANN model named as Model 2; 8 input parameters, namely OP, HP, LP, MOV60, MOV15, RSI, MACD and TRIGGER, have been defined and the BIST100 value has been predicted at the output layer.

To analyze the role of technical indicators precisely, parameters other than input parameters have been kept constant in both ANN models. A total of 97 data sets have been used in the development of ANN models. Analyzing the data to be used in MLP networks is an important parameter that directly affects the prediction performance [25]. For this reason, the prediction performance of ANN models developed by making different data groupings has been analyzed and the model with the highest performance has been optimized. 70% of the data set has been used for training, 20% for validation and 10% for testing. The same methodology has been followed in determining the number of neurons, and after optimizations with different neuron numbers, the model with 10 neurons in the hidden layer has been preferred. As the training algorithm, Levenberg-Marquardt algorithm, which is one of the algorithms used frequently with its high performance, has been used [26-28]. The Tan-Sig function has been used as the transfer function in the hidden layers of the ANN models and Purelin functions in the output layer [29, 30]. The functions used are given below.

$$\mathrm{f(x)} = \frac{1}{1 + \exp(-\mathrm{x})} \tag{1}$$

$$\mathrm{purelin(x)} = \mathrm{x} \tag{2}$$

Mean Squared Error (MSE), coefficient of determination (R) and error rate parameters have been selected in order to analyze the prediction performance of the developed ANN models. The equations used in the calculation of performance parameters are given below [31].

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{X}_{\mathrm{exp(i)}} - \mathrm{X}_{\mathrm{ANN(i)}})^2 \tag{3}$$

$$\mathrm{R} = \sqrt{1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(\mathrm{X}_{\mathrm{exp(i)}} - \mathrm{X}_{\mathrm{ANN(i)}}\right)^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}}\left(\mathrm{X}_{\mathrm{exp(i)}}\right)^2}} \tag{4}$$

$$\text{Error Rate (\%)} = \left[\frac{\mathrm{X}_{\mathrm{exp}} - \mathrm{X}_{\mathrm{ANN}}}{\mathrm{X}_{\mathrm{exp}}}\right] \mathrm{x}\ 100 \tag{5}$$

2.3. Box-Jenkins Models and ARIMA Models

The Box-Jenkins method is one of the statistical forecasting methods used in the forward estimation and control of univariate time series [32, 33]. Developed on the assumption that time-dependent events are random events and time series related to these events are stochastic processes, it is assumed that the time series to which this method is applied is a discrete and stationary series consisting of equally spaced observation values. However, in reality, there is a time-dependent change in the mean and variance of the time series. This change, seen in non-stationary time series, usually occurs with the effect of trend, regular, irregular fluctuations and random fluctuations. For the prediction of non-stationary time series with the Box-Jenkins method, the series should be made stationary with some transformation methods.

Time series models estimated by Box-Jenkins Method are; Autoregressive (AR) Model, Moving Average (MA) Model, Autoregressive-Moving Average (ARMA) Model and Autoregressive Integrated Moving Average (ARIMA) Model. ARIMA models are models that are applied to non-stationary series but converted to stationary by taking differences. Models that are applied to series that are not stationary but have been converted to stationary by the difference process are called "non-stationary linear stochastic models" [34].

It is a combination of AR models, in which the variable is expressed as a function of the t-period and the residual, estimate of the error, in the same period and a certain number of back-period residuals are expressed as a linear function. The general representation of the models is ARIMA (p, d, q). Here, p and q are the degrees of the Autoregressive (AR) Model and the Moving Average (MA) Model, respectively, and d is the degree of difference.

The general ARIMA(p,d,q) model is formulated as follows:

$$Z_t = \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \cdots + \theta_p Z_{t-p} + \delta + a_1 - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots \theta_q a_{t-q}$$

Z_t = The observation values with the difference of d degrees

θ_p = Coefficients for the observation values

a_1 = Residuals (estimates of the errors)

θ_q = Coefficients for residuals

3. Results and Discussion

Figure 1 shows the training performances of the ANN models developed. In the graphs, the changes of MSE values with respect to the epoch are shown. When the graphics are examined, it is seen that the MSE values, which have been at high values at the beginning of the training process, decrease with the advancing epochs and the training process ends when the lowest values, the ideal value, are reached. The low values reached by the MSE values and the intersection of the data obtained from each data set with the best performance line show that the training of the developed ANN models is ideally completed. Examination of error histograms has an important place in analyzing the predictive performance of ANN models. Error histograms showing the errors obtained from each ANN model are given in Figure 2. When histograms are examined carefully, it is seen that the error values obtained from each data set are located close to the zero error line. However, it should be noted that the numerical values of the errors expressing the ANN predictions and target data are also very low. These data obtained from the error histogram graphs show that the developed ANN models are developed in such a way that they can predict BIST100 values with very low error rates. When we compare the models by ignoring the extreme values, the error values are smaller in the first one, where the RSI and MACD indicators are not added. Besides, the distribution of error values in the first model are closer to the normal distribution, while the distribution of the second model to which the indicators are added is rather steep and this model has got more extreme error values.

Figure 3 shows the realized BIST100 values and the values obtained from the ANN model. When the graphs are examined, it is seen that the prediction data obtained from both ANN models developed with different input parameters are in a very good agreement with the realized values. This perfect agreement of the data points shows that both ANN models have been developed to predict BIST100 values with high accuracy. While the values realized on the x-axis of Figure 4 are located, on the y-axis there are the predicted values obtained from the ANN model. Besides, the data points in the graphics located very close to the equality line. The proximity of the data points to the equality line shows the proximity of the predicted values obtained from the ANN model to the realized values, which are the target data.

In the study, an ARIMA model is estimated to compare with the performance of ANN models. Among different ARIMA models, the ARIMA (2,1,2) model, details are given in Table 2, performed best. Figure 5 and Figure 6 show the prediction data from the ARIMA model. The figures show that the ARIMA model makes successful predictions. However, when compared with ANN models, the predicted and actual data are not as close to each other as in ANN models.

Figure 7 shows the error rates calculated using equation 5. When the error rates calculated for each data point are examined, it is seen that the data points calculated for both models are close to the zero error line. When the error rates are analyzed in detail, it is seen that the average error rate of Model 1 is 0.00014%, while the average error rate of Model 2 is -0.00713%. Considering that the error rates calculated for both models are very low, it is concluded that both ANN models can predict BIST100 values with very low error. However, when the mean values are analyzed, it is seen that Model 1 has a lower error rate compared to Model 2. Nevertheless, the fact that the errors of the second model are almost zero between the 40th and 80th values in the second model, we can say that the indicators strengthen the prediction. When the graphics are observed, it is seen that the predictions made with the intraday data are stronger between 13:00 and 16:30. In general, the prediction performance obtained from the first model, which does not use RSI and MACD indicators, is higher than the second model. However, it is clear from the graphs that the second model can make predictions with values close to zero error between 13:00 - 16:30 hours. Empirical studies on intraday returns show that the trading volume, volatility, price difference and returns of stocks reach their highest levels in the first and last half hours of the trading day [31]. The weakening of the predicted values obtained after the 80th value is related to the approaching closing time of the stock market.

In Figure 8, the target values and the difference values obtained from the ANN models are given for each data point. As can be seen from the graph, the difference values calculated for both ANN models have very low values. Calculation of the differences so low confirms that the ANN models can predict with very low errors. The findings obtained from the difference values indicate that the models achieved a more successful prediction accuracy between the 40th and 80th observations. In this range, especially the data of the second model is much closer to zero. This interval is approximately between 13:00 and 16:30. It is also seen that the predictive power of the models decreases with the closing time of the stock market approach.

In Figure 9, the graphs expressing the average values of the error rates calculated for Model 1 and Model 2 are shown. When the graphs obtained from the data points are examined, it is seen that the graph obtained from Model 1 has a trend closer to the zero error line. In Figure 10, histogram graph of the minimum, maximum and average values of the error rates of Model 1 and Model 2 is given. As can be seen from the graphics, the error rates of Model 1 have lower values than Model 2. Figure 11 and Figure 12 give the information on residuals (estimates of the errors) in the ARIMA model. The residuals of the ARIMA model take a maximum value of 12.4 and a minimum of -15.45. In the ARIMA model, the residuals are concentrated between -5 and +5, while the error rates in the ANN models are usually between -0.05 and 0.05. The results regarding the predictions clearly show that the ANN models are more successful than the ARIMA model.

4. Conclusion

The proliferation of digital technology has altered the investment decision techniques for financial professionals. Mostly and increasingly, investment decisions are made by new instruments as artificial intelligence using algorithms in seconds. In this study, two different ANN models have been developed to analyze the role of technical indicators in intraday predicting of stock markets. For this purpose, two different ANN models have been developed in which different parameters are defined in the input layers to analyze the role of technical indicators in predicting intraday stock markets. In Model 1, 5 input parameters OP, HP, LP, MOV60, and MOV15, have been defined and BIST100 value has been predicted at the output layer. In Model 2, 7 input parameters are defined as OP, HP, LP, MOV60, MOV15, RSI, MACD, and TRIGGER and the BIST100 value has been predicted at the output layer. The prediction values obtained from MLP network models developed with a total of 97 data sets have been compared with the target data and together with this, the predictive performance of the models has been analyzed by calculating the performance parameters. Studies on performance analysis of developed ANN models have shown that both ANN models can predict the BIST100 values with very low error rates. However, Model 1, which has been developed with fewer input data identified, also appears to have higher predictive performance compared to Model 2. The main reason for studying with these two models, both of which are very successful in predicting the BIST100 index, is to examine the effect of RSI and MACD indicators on the predictive power of the model. The results support that the predictions made with intraday data are stronger between 13:00 and 16:30 hours. In general, the first model, which does not use RSI and MACD indicators, is more successful than the second model, but the second model predicts with almost zero errors in the 13:00 - 16:30 hour range. Moreover, an ARIMA model is also estimated with the BIST100 index and the results are compared with the ANN models. Predicted values and errors showed that the ANN models perform significantly better. The proposed ANN models using technical indicators can be used in algorithmic trading systems and help investors predict market trends and find the right time to trade. This study examining the effect of the indicators, which are frequently used by financial professionals in technical analysis, might be tested for different data ranges and different stock markets in future studies.

Data availability statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Andaç Batur Çolak

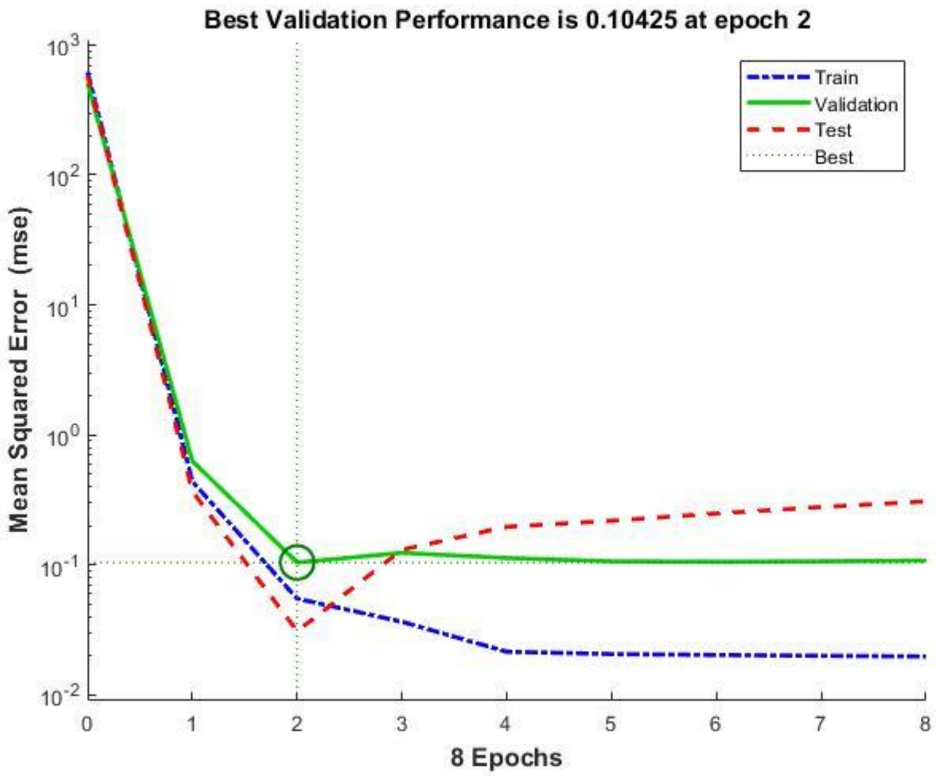
In 1999, he graduated from Niğde University, Faculty of Engineering, Department of Mechanical Engineering. In 2004, he received his master's degree with his thesis on "Pre-warning dynamic maintenance in industrial systems" in the Department of Energy at the Institute of Science at Mustafa Kemal University and in 2020 he received his PhD degree with his thesis on "Modeling Thermo physical Properties of a Hybrid Nanofluid by Artificial Neural Network and Experimental Investigation" in the Department of Energy at the Institute of Science at Niğde Ömer Halisdemir University and received Associate Prof. Dr. degree in 2021. He has been working as an executive at various levels in the energy sector since 2000. He is also a Member of the Advisory Board at Istanbul Commerce University, Information Technologies Application and Research Center.

Ayben Koy

After graduating from The Faculty of Economics in Istanbul University in 2004, she has worked 8 years in the finance sector and other sectors. She started to work at Istanbul Commerce University in 2012. Having completed her Master of Business Administration at Yıldız Technical University, she became a Doctor of Philosophy Finance with her thesis on Derivative Markets at Istanbul University in 2016. She received the Associate Professor title in 2018. She has written two books on Derivative Markets, is the co-author of a book on Financial Econometrics and many studies in the field of finance. She provides consultancy and training to institutions and businesses in various fields of finance as financial management and risk management and continues in business life along with her academic studies. She is still working as the Dean of The Graduate School of Finance at Istanbul Commerce University.

Figure and Table Captions

Figure 1: Training performances of the ANN models a) Model 1 b) Model 2



a)

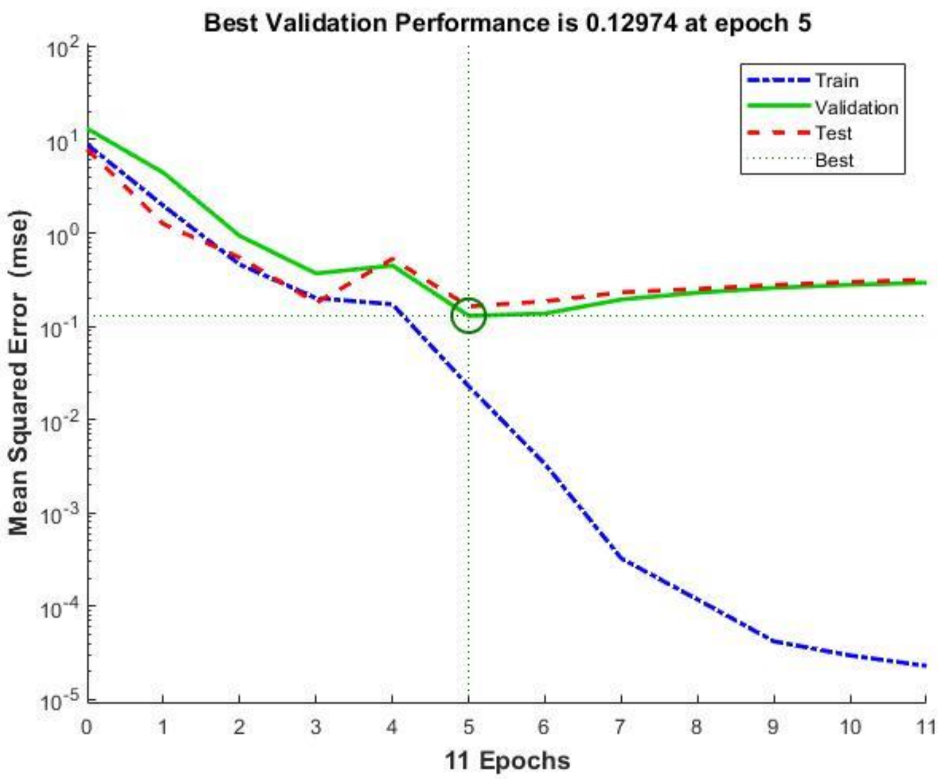


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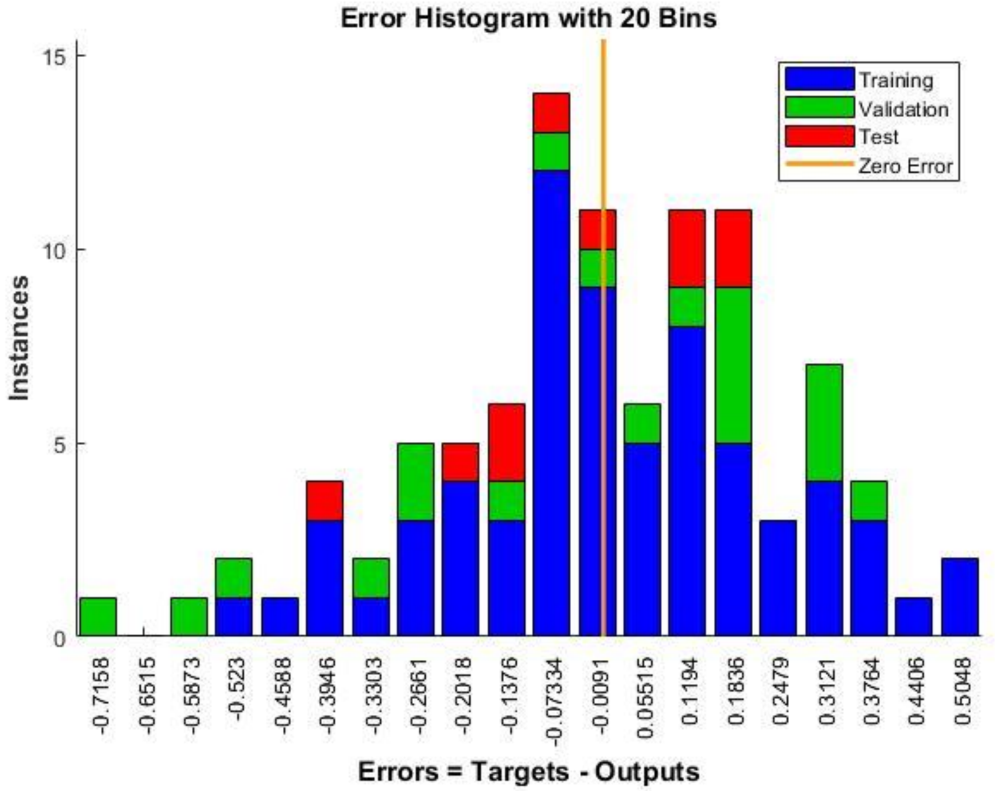
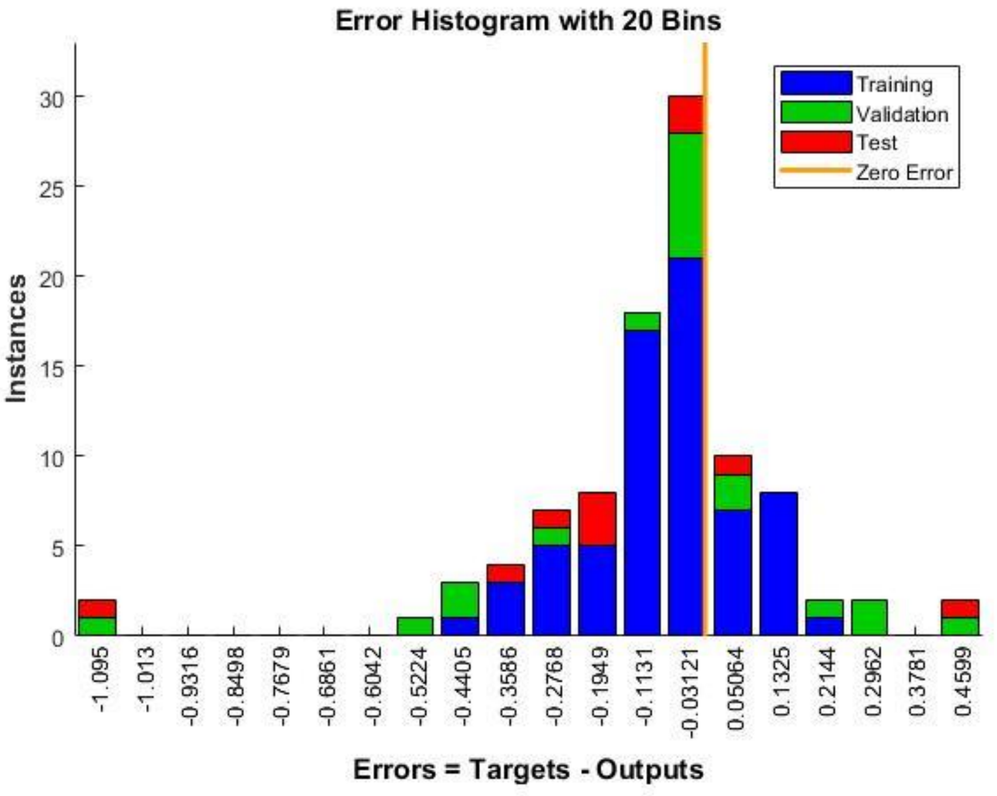
Figure 1. Training performances of the ANN models a) Model 1 b) Model 2



a)



b)

Figure 2. Error histogram of the ANN models a) Model 1 b) Model 2

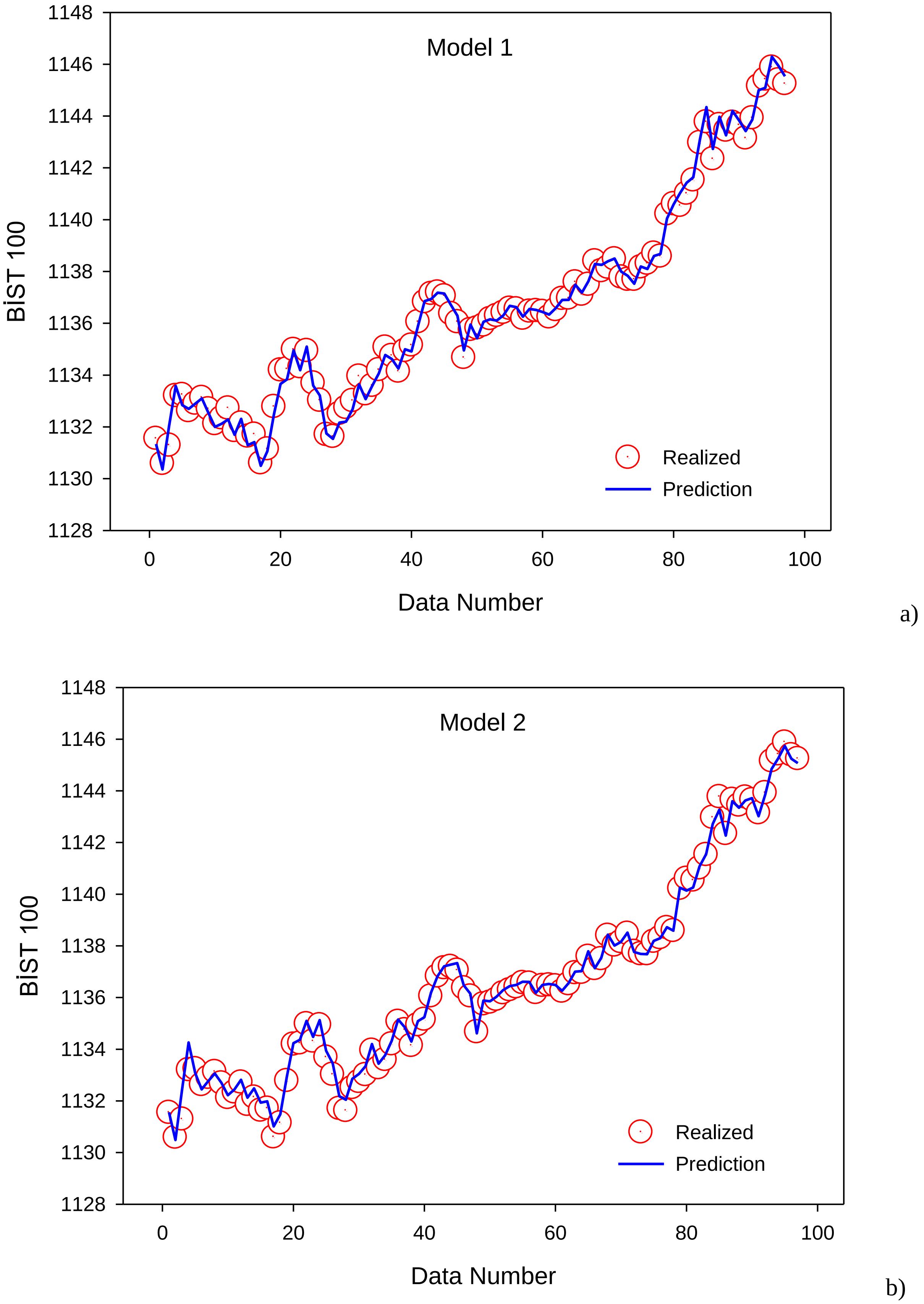
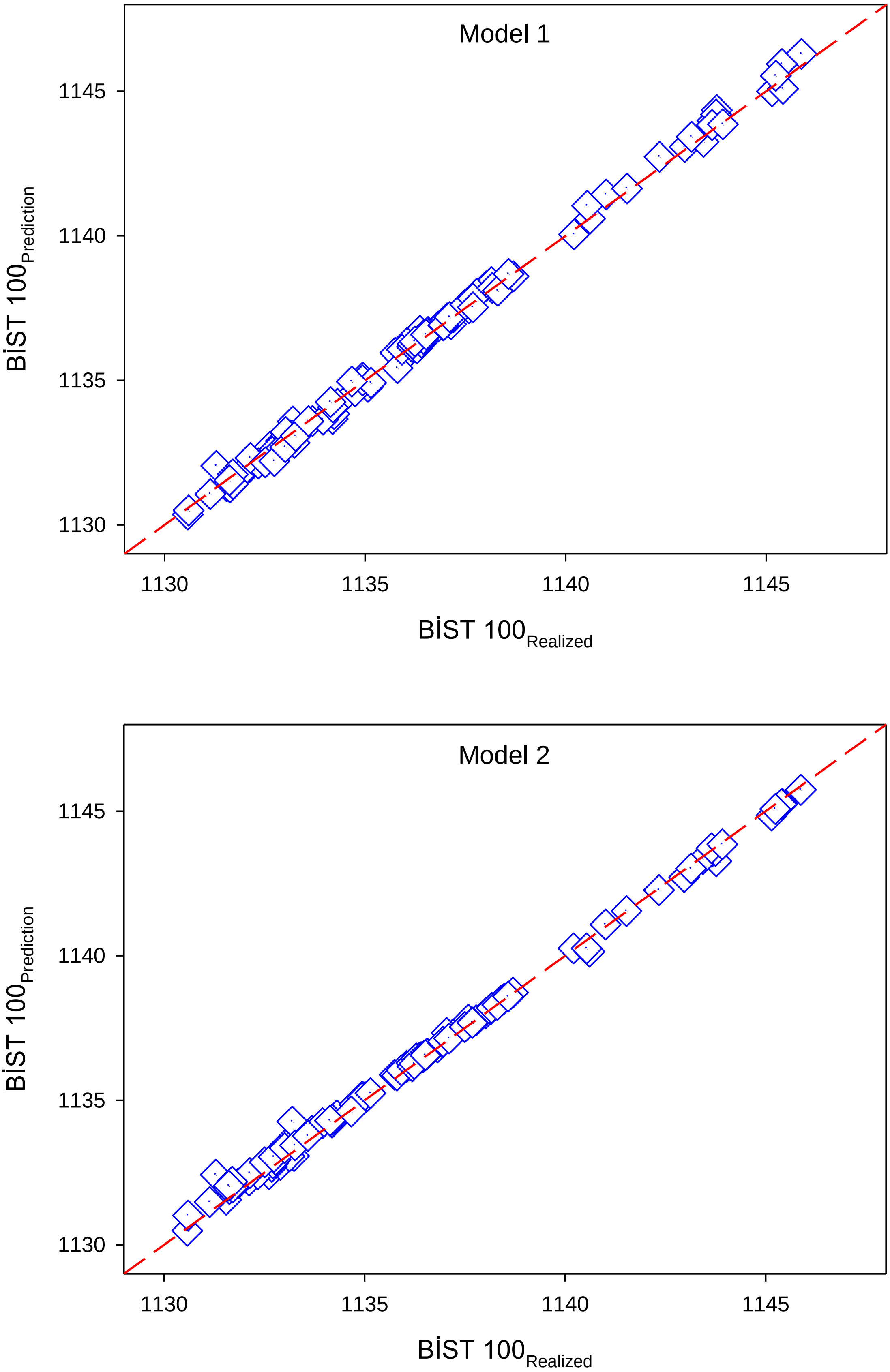


Figure 3. Realized and predicted BIST100 values a) Model 1 b) Model 2



a)

b)

Figure 4. ANN prediction vs realized data a) Model 1 b) Model 2

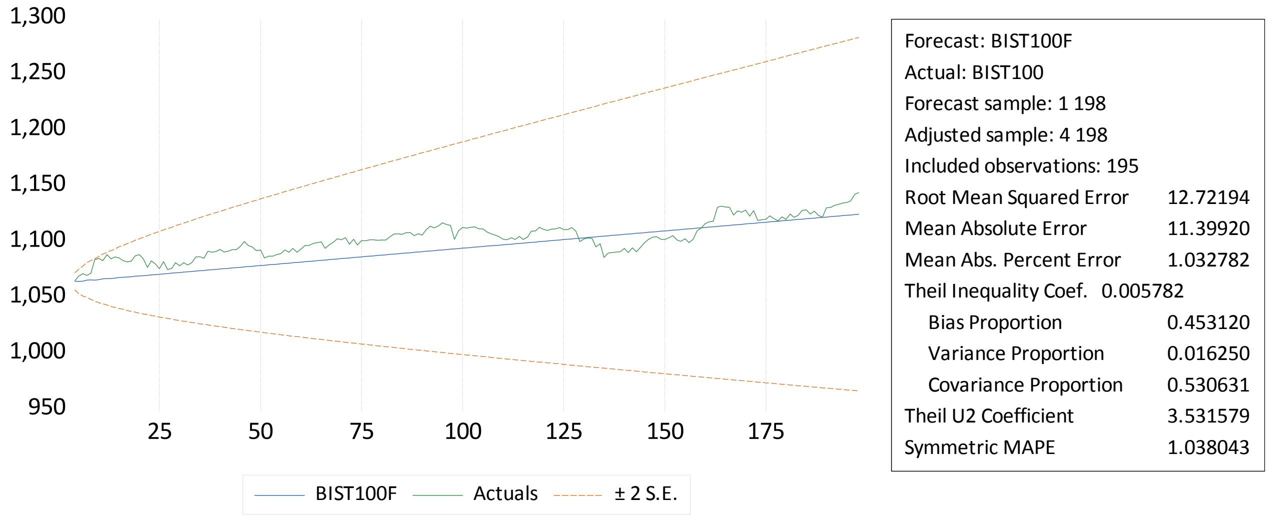


Figure 5. Dynamic Forecast for ARIMA (2, 1, 2)

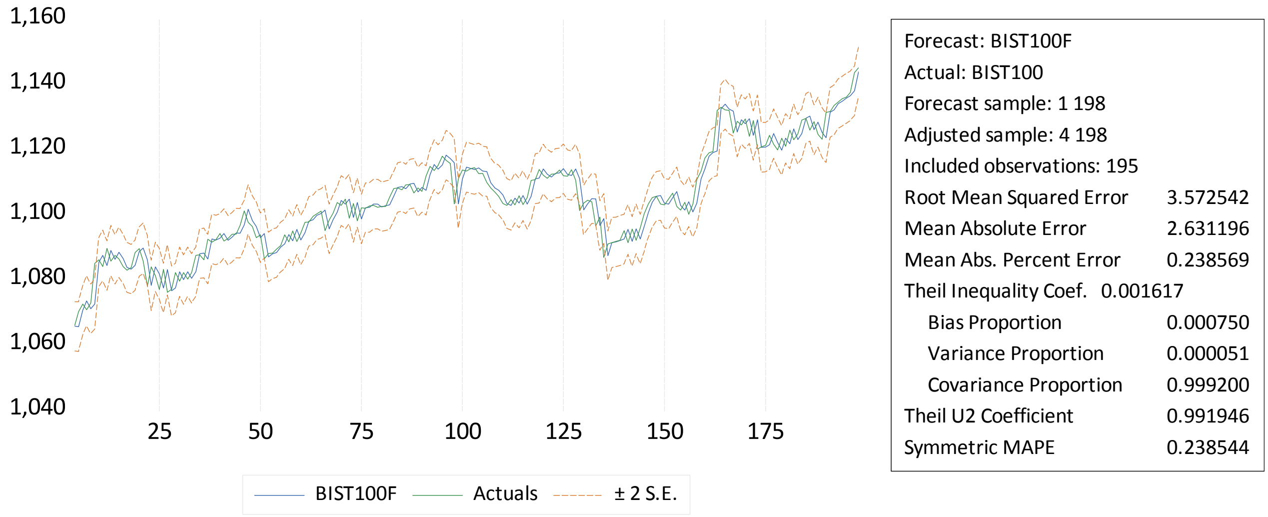
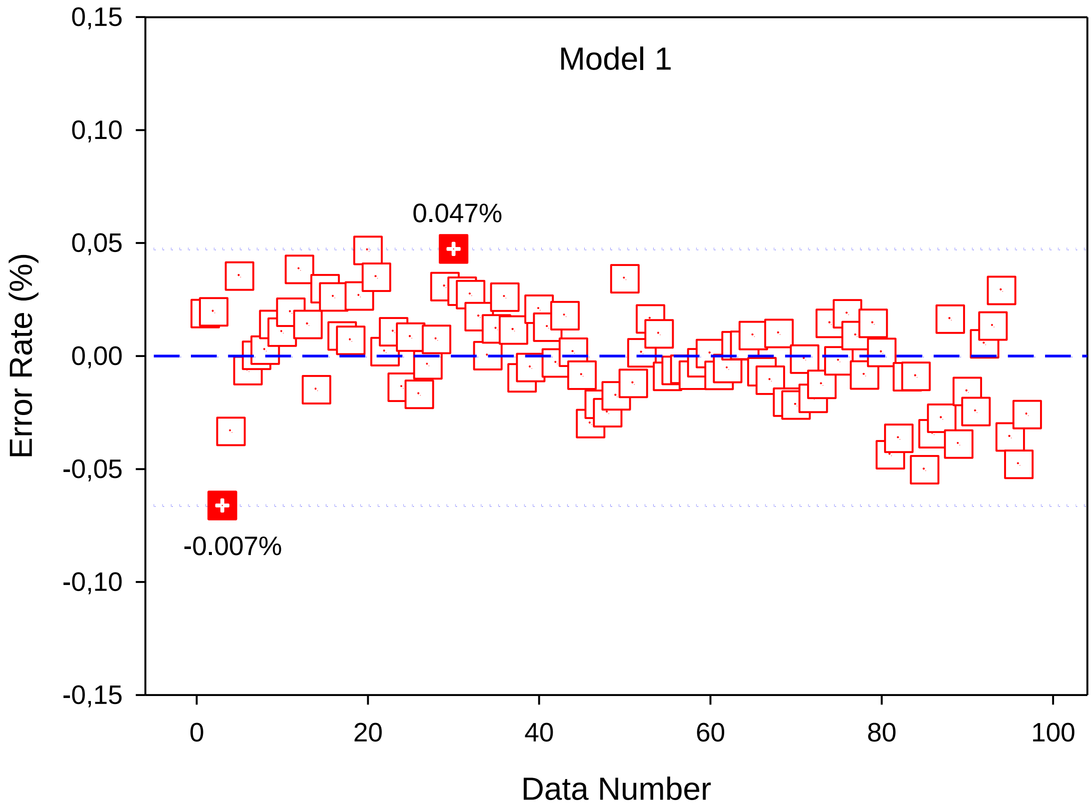
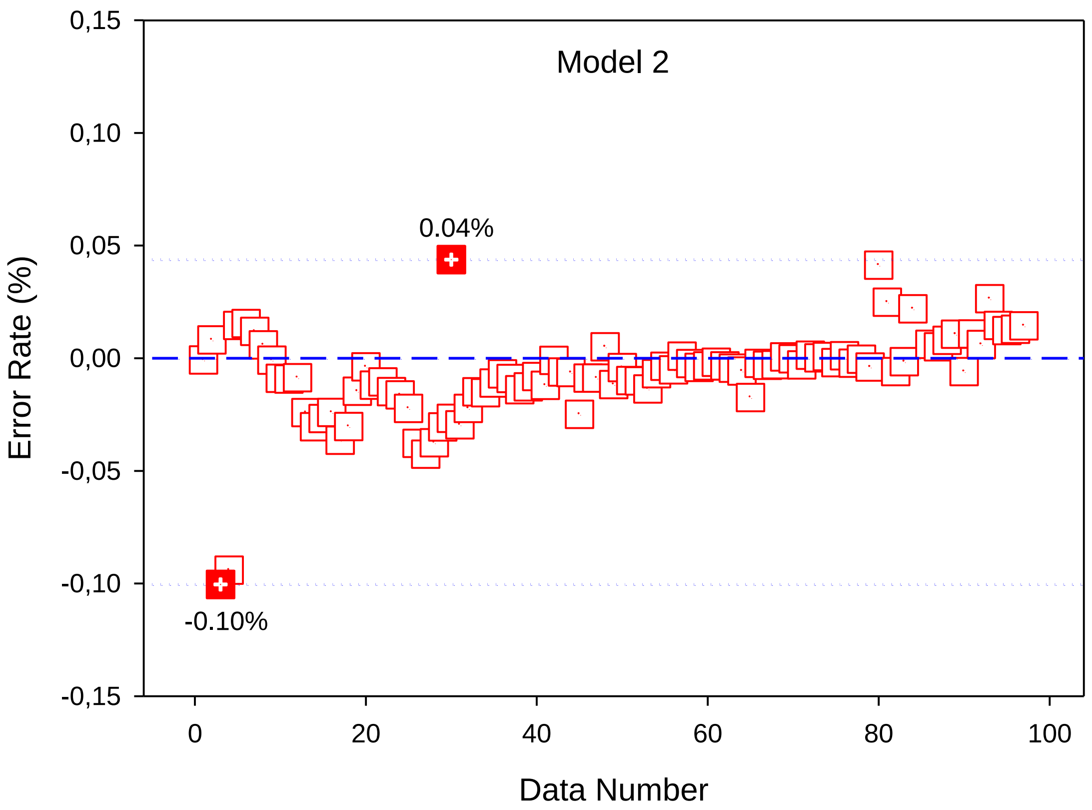


Figure 6. Static Forecast for ARIMA (2, 1, 2)



a)



b)

Figure 7. Error rates according to data number a) Model 1 b) Model 2

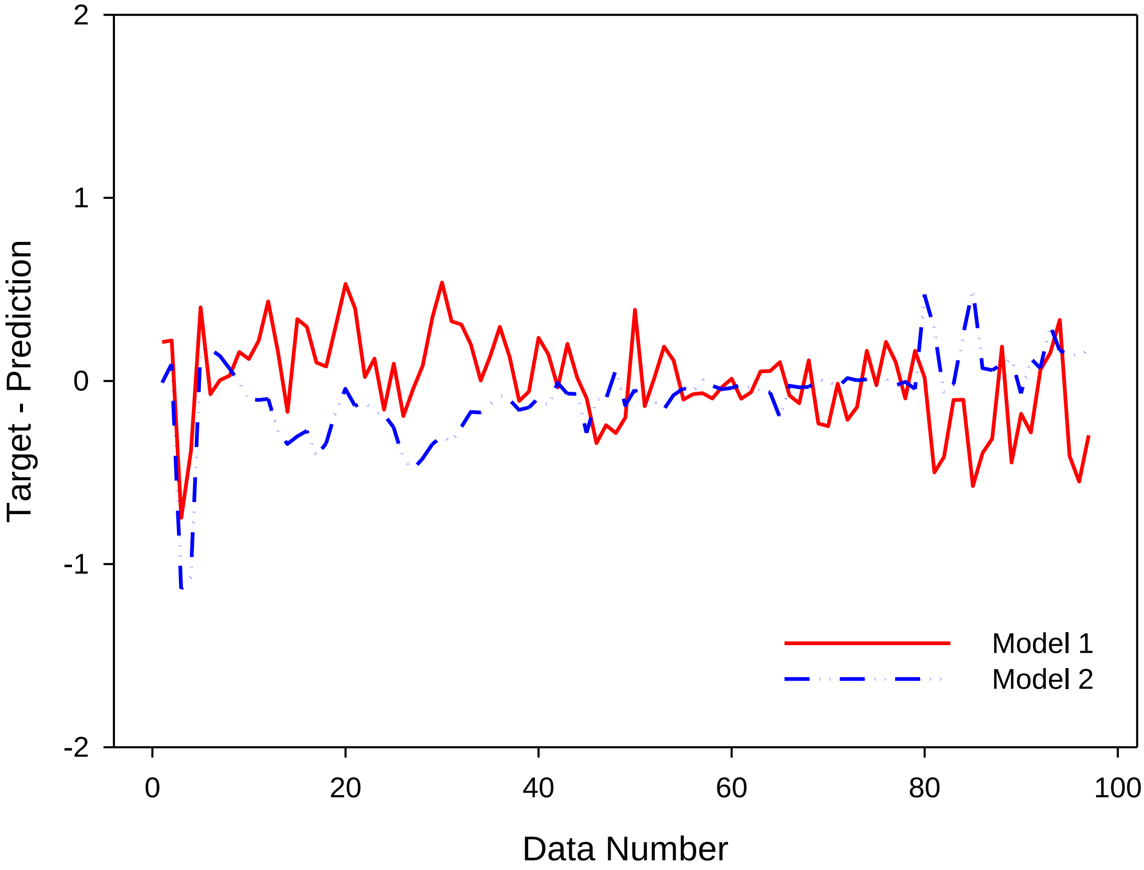


Figure 8. Difference values between target and prediction values

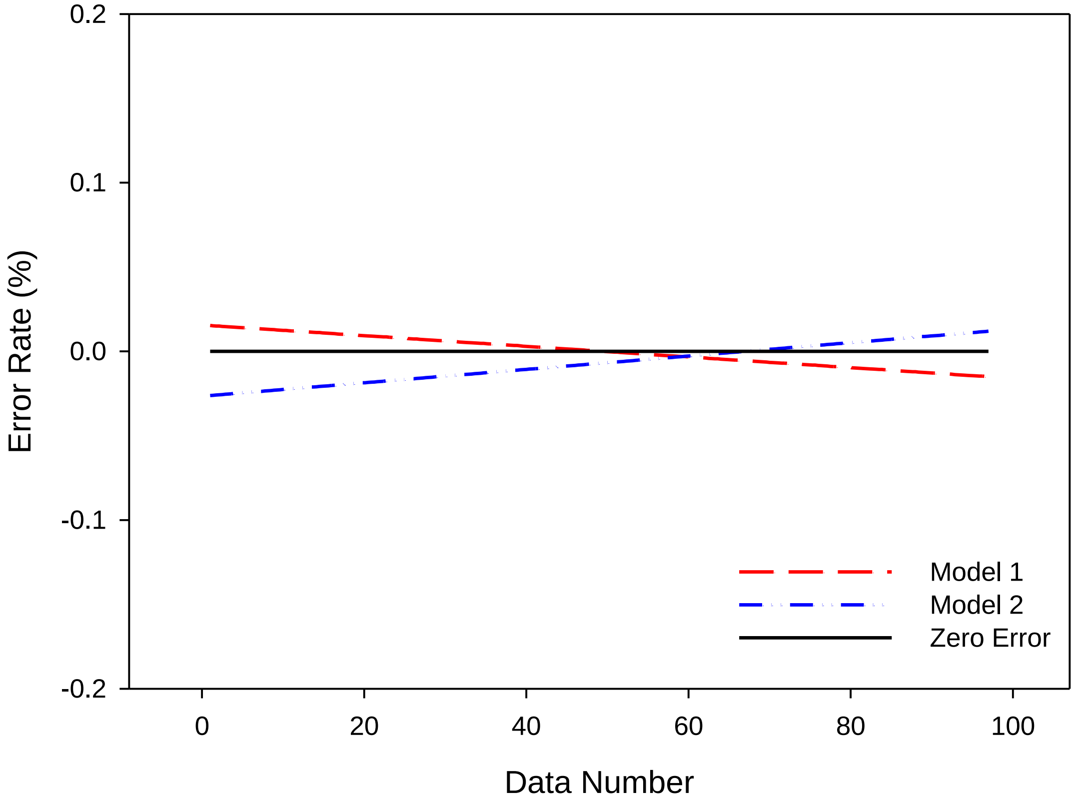


Figure 9. Average error rates for ANN models

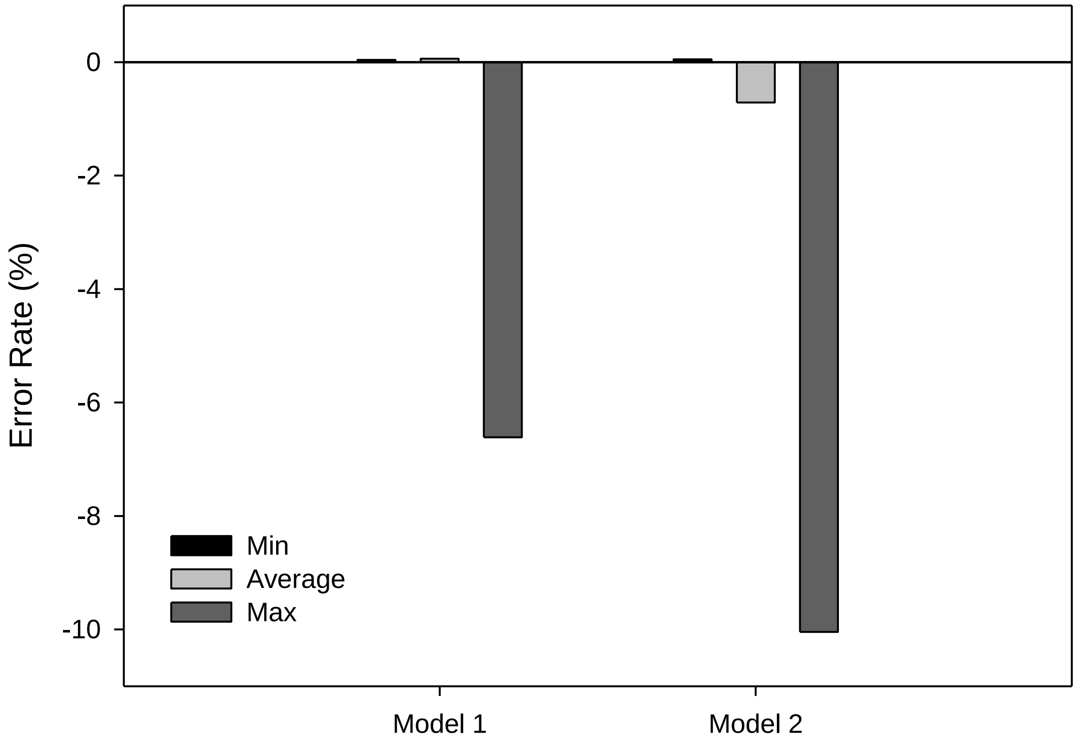


Figure 10. Error rates histogram for ANN models

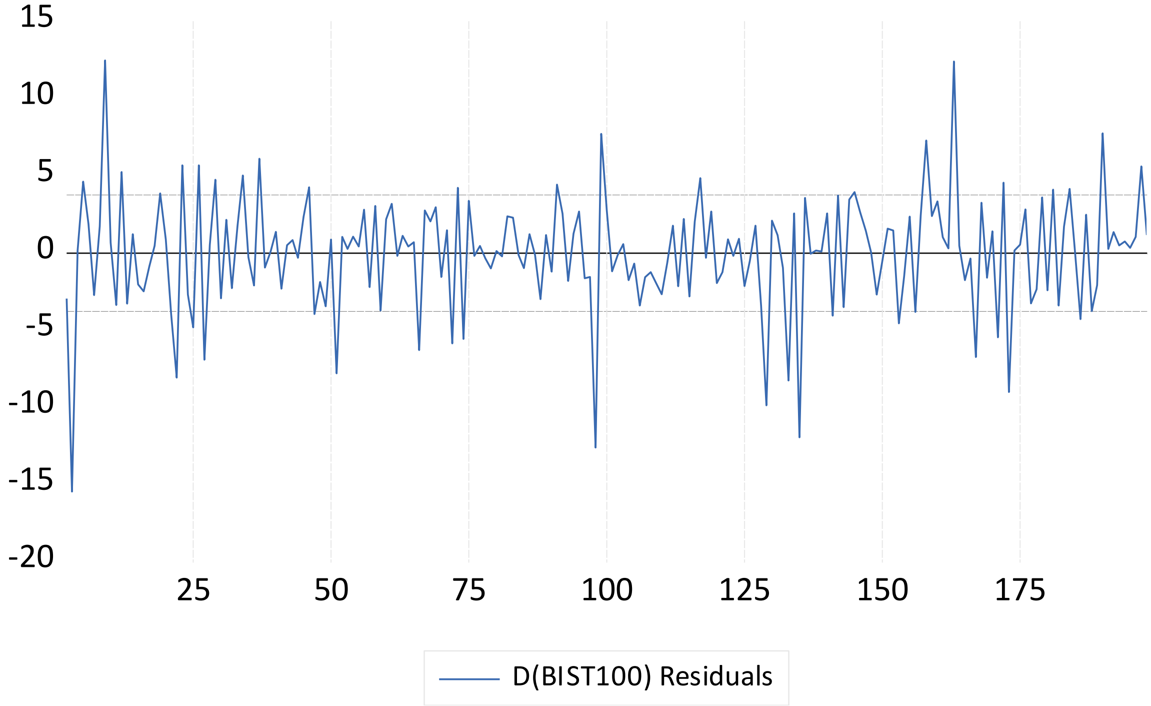


Figure 11. Residuals (Estimates of the Errors) for ARIMA (2, 1, 2)

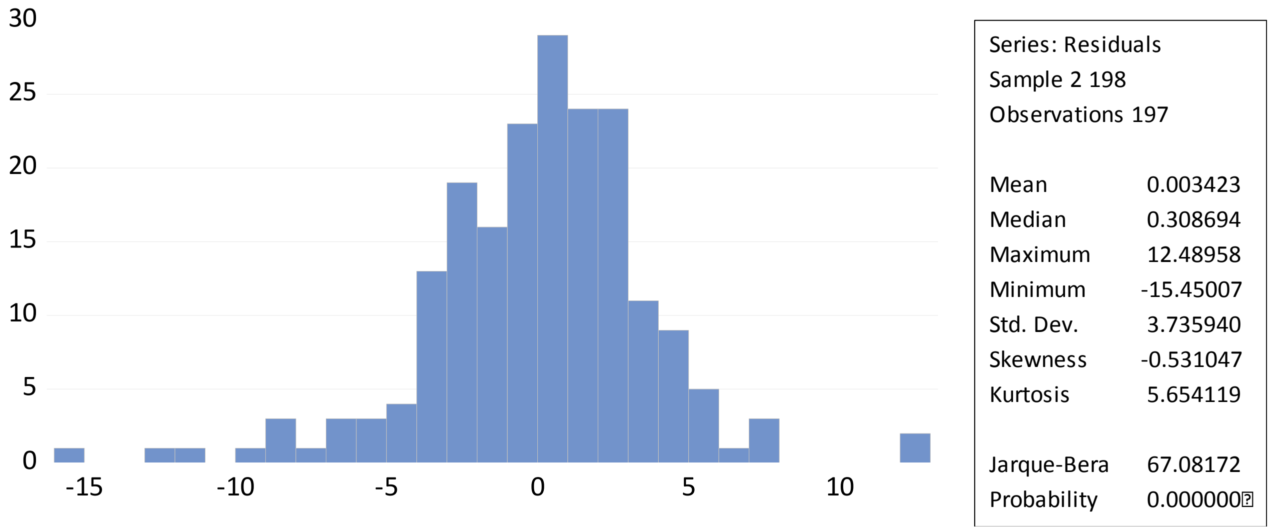


Figure 12. Residuals' Histogram for ARIMA (2, 1, 2)

Table 1. Variables used in the study

Variables		Source
BIST100 Closing Price	BIST100	Matriks IQ
BIST100 Opening Price	OP	Matriks IQ
BIST100 Highest	HP	Matriks IQ
BIST100 Lowest Price	LP	Matriks IQ
15 minutes Moving Averages	MOV15	Matriks IQ
60 minutes Moving Averages	MOV60	Matriks IQ
The Relative Strength Index	RSI	Matriks IQ
The Moving Average Convergence Divergence	MACD	Matriks IQ
The Moving Average of MACD	TRIGGER	Matriks IQ

Table 2. ARIMA (2, 1, 2) Model – BIST100

Variable	Coefficient	Standard Error	t-Statistic	Probability
constant	0.310365	0.297973	1.041588	0.2989
AR (2)	-0.793602	0.336344	-2.359499	0.0193
MA(2)	0.837575	0.307367	2.725001	0.0070
SigmaSQ	13.88641	0.949886	14.61902	0.0000