ACTA INFOLOGICA 2021;5(2):241-254
dergipark.org.tr/acin

İSTANBUL UNIVERSITY PRESS

DOI: 10.26650/acin.907990

RESEARCH ARTICLE

Forecasting of Turkish Sovereign Sukuk Prices Using Artificial Neural Network Model*

Türkiye'de Hazine Sukuk Fiyatlarının Yapay Sinir Ağı Modeli ile Tahmini

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ABSTRACT

Recently, artificial neural networks have been successfully applied in many areas such as forecasting financial time series, predicting financial failure, and classification of ratings. However, it has hardly been applied in forecasting sukuk prices, which is considered the most common Islamic capital market instrument. Since sukuk is a new financial asset, there are not enough studies in this area. Therefore, this study aims to forecast the Turkish sovereign sukuk prices using with artificial neural network model and to reveal the determinants in the forecasting of sukuk prices. For this purpose, a multi-layer feed forward artificial neural network model is designed using dollar-based international sovereign sukuk price data issued by the Turkish Ministry of Treasury and Finance. The dollar index, volatility index, geopolitical risk index, Standard and Poor's Middle East and North Africa sukuk index, and Eurobond prices constituted as input variables of the designed model and the sovereign sukuk prices formed the output. As a result, the sovereign sukuk prices were forecasted accurately at the success rate of 99.98%. The accurate forecasting of sukuk prices will play a critical role in reducing the risk perception of sukuk investors and increasing their profitability. The findings of the study are important in terms of proving that the artificial neural network model is an effective model for forecasting the sukuk prices and revealing that the dollar index, volatility index, geopolitical risk index, Standard and Poor's MENA sukuk index, and Eurobond prices are determinants in forecasting sukuk prices.

Keywords: Sukuk, Price Forecasting, Artificial Neural Network, Geopolitical Risk, Dollar Index, Volatility Index

ÖZ

Son yıllarda yapay sinir ağları, finansal zaman serilerinin tahmini, finansal başarısızlığın öngörülmesi ve derecelendirme notlarının sınıflandırılması gibi birçok alanda başarıyla uygulanmaktadır. Bununla birlikte, İslami sermaye piyasalarının en yaygın ürünü olarak nitelendirilen sukuk fiyatlarının tahmininde hemen hemen hiç uygulanmamıştır. Sukuk yeni bir finansal varlık olduğu için bu alanda yeterli çalışma bulunmamaktadır.. Bu nedenle çalışmada, Türkiye'deki hazine sukuk fiyatlarının yapay sinir ağı modeli ile tahmin edilmesi ve sukuk fiyatlarının tahminindeki belirleyicilerin ortaya konulması amaçlanmaktadır. Bu amaç doğrultusunda, Türkiye Hazine ve Maliye Bakanlığı tarafından ihraç edilen dolar bazlı uluslararası hazine sukuk fiyat verileri kullanılarak çok katmanlı geri beslemeli yapay sinir ağı modeli oluşturulmuştur. Dolar endeksi, volatilite endeksi, jeopolitik risk endeksi, Standard and Poor's MENA sukuk endeksi ve Eurobond fiyatları geliştirilen modelin giriş değişkenlerini, hazine sukuk fiyatı ise modelin çıkışını oluşturmuştur. Sonuç olarak, hazine sukuk kapanış fiyatları tasarlanan model ile %99,98 başarı oranıyla doğru tahmin edilmiştir. Sukuk fiyatlarının yüksek başarıyla tahmini, sukuk yatırımcılarının risk algılamasının azaltılmasını ve kârlılığının artırılmasını sağlamada etkin bir rol oynayacaktır. Çalışmanın bulguları, yapay sinir ağı modelinin sukuk fiyatlarını tahmin etmede etkin bir model olduğunu kanıtlaması ve dolar endeksi, volatilite endeksi, jeopolitik risk endeksi, Standard and Poor's MENA sukuk endeksi ve Eurobond fiyatlarının, sukuk fiyatlarını tahmin etmede belirleyici olduğunu ortaya koyması bakımından önem taşımaktadır.

Anahtar Kelimeler: Sukuk, Fiyat Tahmini, Yapay Sinir Ağı, Jeopolitik Risk, Dolar Endeksi, Volatilite Endeksi

* This study is derived from the doctoral thesis titled " Sukuk in Islamic financial system: Forecasting sukuk prices in Turkey with artificial neural network model" which written by Dilşad Tülgen Çetin with advisor Assoc. Prof. Dr. Osman Tuğay.

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Submitted: 01.04.2021
Revision Requested: 07.06.2021
Last Revision Received: 10.06.2021
Accepted: 16.06.2021
Published Online: 13.12.2021

Citation: Cetin, D. T., & Metlek, S. (2021). Forecasting of Turkish sovereign sukuk prices using artificial neural network model. *Acta Infologica, 5*(2), 241-254. https://doi.org/10.26650/acin.907990

1. INTRODUCTION

The Artificial Neural Network (ANN) is a soft computing model developed mathematically by imitating the learning process of the human brain. Its ability of modelling complex relationships and problems besides its outstanding success in prediction and classification has made ANN a widely used application in every field, including military, health, industrial, and finance applications.

ANN is able to produce very accurate results that cannot be achieved with linear models in predicting financial data, which is one of the most critical requirements of the finance sector (Dhamija & Bhalla, 2010; Hossain et al., 2009; Qian, 2017). This capability causes it to be applied to more topics in finance day-by-day and to be developed through new hybrid models. In recent years, studies in finance show that ANN has produced successful results in loan evaluations, firm failure, and bankruptcy prediction, optimal capital structure estimation, forecasting of financial assets prices, firm valuation, financial planning, and performance (Özbayoglu et al., 2020; Xu et al., 2020a; Zhang et al., 2020).

There is a massive literature on using ANN for forecasting financial data series such as stock index, exchange rate, gold, and oil prices, etc. (Aslam et al., 2020; Singh & Srivastava, 2017; Tealab et al., 2017; Xu et al., 2020b). On the other hand, there are specific topics in finance where limited studies have been conducted with ANN models. Sukuk market, the most common and the newest financial instrument of Islamic capital markets, is one of them. It can be said that very little mathematical and Artificial Intelligence (AI) analyses have been done in sukuk markets, partly due to limited data, but also due to challenges of availability and validity of sukuk data. In previous studies, it is seen that ANN is used to classify sukuk credit risk rating (Arundina et al., 2015, 2016; Ismail & Arundina, 2019), however, interestingly, it is almost never used for forecasting sukuk prices.

Elicited by this research gap, this study primarily aims to forecast sukuk prices using the Multi-Layer Feedforward (MLF) artificial neural network model. The secondary aim of the study is to assign the factors that may affect sukuk prices as input variables and to discover whether these inputs are determinants of sukuk price forecasting.

The originality of the research is that it is the first application of ANN to forecast sukuk prices in Turkey. In addition, it is presumably the first study that reveals the determinants of sukuk price forecasting in the international literature. This paper is important in terms of setting a reference for future studies to be accomplished on the forecasting of sukuk prices.

2. LITERATURE

2.1. Sukuk Market

Sukuk has recently become one of the most remarkable financial services in Turkey and the world. Sukuk, aims to structure capital market instruments in accordance with Islamic principles. These are certificates issued on the basis of tangible assets that represent undivided ownership rights over them (AAOIFI, 2015). The assets that form the sukuk issuance basis are transferred to an institution called a special purpose vehicle (SPV) that acts as a trustee on behalf of sukuk investors. Since the SPV also has the issuer's title, it issues sukuk based on the underlying assets transferred to it by the obligor. It provides financing by paying the proceeds from the issue to the obligor as the cost of the assets. Compliance with Islamic principles at all stages, from the issuance of sukuk to the transfer of income, is documented with the fatwa's approval (Çetin, 2020).

Sukuk is seen as a more reliable financing instrument than interest-based financial instruments due to its asset-based issuance and profit/income-sharing principles. These principles lead sukuk to be low-risk, low-cost, low-volatile, and thus a stable stance even in economic turbulence. Furthermore, sukuk is a suitable financial instrument for raising funds from Gulf countries, causing it to receive progressively increasing demand in the global financial markets (Çetin, 2021).

Sukuk is divided into two categories according to the type of issuer. Sukuk issued by the treasury to meet the public financing needs of countries are entitled sovereign sukuk, whereas sukuk issued by participation banks and companies are corporate sukuk. Secondary trading of sukuk in Turkey is mostly dominated by sovereign issues. Since the legal regulation on the issuance of sukuk in public financing is made for the Ijara Sukuk (based on rental income) type of sukuk, all sovereign sukuk issues were realized in Ijara Sukuk.

The first sukuk issues in the world were realized in Malaysia in 1990, but there was no significant development in the sukuk markets for 11 years. Sukuk markets grew rapidly after 2001. The global sukuk market, which was 1.1 billion dollars in 2001, reached 145.7 billion dollars, and the amount of outstanding sukuk reached 543.4 billion dollars in 2019 (IFSB, 2020). In Turkey, in 2010, with the first corporate sukuk issuance and in 2012, the first sovereign sukuk issuance, a total of $ 48 billion worth of sukuk were issued in the period of 2010-2020. The Turkish sukuk market reached a volume of $ 13.26 billion in 2019, ranking fourth in the global sukuk market with a share of 9% (TKBB, 2020). Considering the geopolitical position, booming economy, and capital market processes, it is incontrovertible that Turkey has great potential in the global sukuk market.

Alongside the increasing interest of sukuk markets, the significance of the risks posed by secondary markets increases for investors. In developing countries, including Turkey, along with geopolitical risk, currency risk, and interest rate risk, the volatility of capital markets is also high. Despite the fact that the sukuk markets are less affected by these risks than interest-based capital market instruments, they are still exposed to all these risks. At this point, price forecasting has critical importance in minimizing the risk of sukuk markets. The forecasting of sukuk prices offers investors significant advantages such as maximizing profits or minimizing losses and hedging risks (Çetin, 2020).

2.2. Literature Review

In the literature, it is seen that the number of studies forecasting sukuk prices is quite low and the use of the ANN model in sukuk markets is limited to a few studies. In previous sukuk price prediction studies, it is seen that a binomial decision tree (Wardani et al., 2020), and K nearest neighbourhood (K-NN) algorithms (Yiğiter et al., 2018) are used. On the other hand, only one study was found that specifically forecasts the sukuk prices using the ANN model (Hila et al., 2019). However, it is worth mentioning the studies using the ANN model in the index forecasting of Islamic stock (Siddiqui & Abdullah, 2017) and sukuk rating classification (Arundina et al., 2015, 2016), even if it is not used to directly forecast sukuk prices. These studies are briefly explained in their chronological order as follows:

Wardani et al. (2020), forecasted the sovereign sukuk returns, that the state issued for financing the research and development activities in Indonesia, under different price scenarios (continuity, abandonment, and substitution scenarios) with a binomial decision tree approach. The results stated the consistency in the risk-return balance and revealed that the predictive values closest to current project-based sukuk returns were obtained in a full-continuity scenario.

Hila et al. (2019), used the Moving Average MA (p)’s information parameter as an input layer of the ANN algorithm in order to estimate the sukuk data. The results revealed that the moving average-ANN algorithm provides the best performance in terms of accuracy and it is more reliable to use it in the medium term to forecast sukuk data.

Yiğiter et al. (2018), forecasted Vakıf Portfolio’s sukuk prices using the K nearest neighbourhood (K-NN) algorithm. As a result of the analysis, in the forecasting made for one, three and five days ahead with the K-NN models, success was 98%, 96%, 94%, respectively. This study, which is the first using the K nearest neighbourhood method in sukuk prices data, reveals the suitability of the method for financial problems.

Siddiqui and Abdullah (2017), used a multilayer perceptron ANN model to forecast the Islamic and conventional stock index returns of Saudi Arabia, Oman, UAE, GCC, BRICS and the EU Region. The results revealed that the macroeconomic variables used in the forecast model produced more accurate results in predicting Saudi Arabia, Oman and UAE stock prices.

Arundina et al. (2016, 2015), used Multinomial Logistic Regression (MLR) and ANN models to create a sukuk credit rating prediction model from various financial variables. In sukuk rating, it has been determined that ANN obtained a higher accuracy rate (96.18%) than MLR (91.72%).

Considering the very few eligible articles, it is obvious that further studies are needed on this subject. Therefore, the main motivation for this paper has been to fill this gap in the literature.

3. MATERIAL

Within the scope of the research, in order to obtain the longest-term data, the dollar-based ten-year international Turkish sovereign sukuk issued on 24.11.2014 was selected as the sample of the study. The data period was limited between the dates of 24.11.2014, which is the first issue date of the sovereign sukuk, and 22.01.2020, the date when the data were analyzed. Data that could not be provided due to missing data and differences in vacation dates were removed from the data set and as a result, 1282 daily data were obtained.

The factors that may affect the dollar-based sovereign sukuk prices, which were selected as the inputs of the ANN model, were determined based on correlation analysis and the previous studies. There are many studies in the literature comparing sukuk and bonds to analyse the relationship between them with several models, such as regression, correlation, and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) (Alam et al., 2013; Ariff et al., 2017; Godlewski et al., 2013; Keten, 2016; Mohd Saad et al., 2019; Raei & Cakir, 2007). All of the studies reveal a high relationship between sukuk and conventional bonds. Considering the studies investigating the risk factors affecting Islamic capital markets, few studies draw attention. Examining the risk factors that cause price movements in Islamic capital markets, Hatipoğlu and Sekmen (2018) revealed in their studies that the US Dollar Index (DXY), and the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), significantly affects the risk level of the global Islamic capital markets. Çetin (2019) used the Geopolitical Risk (GPR) index to represent the geopolitical risk in investigating the causality relationship between the price movements of Islamic capital markets in Turkey and geopolitical risk. In the light of previous studies, the correlation between sovereign sukuk prices and the factors that can affect its price movements were analysed. The correlation analysis results are displayed in Table 1.

Table 1

Correlation analysis of sovereign sukuk with the input variables

	Eurobond	**S&P Sukuk**	**DXY**	**GPR**	**VIX**
Sovereign Sukuk	*0,96*	*-0,37*	*-0,22*	*-0,22*	*-0,11*

Table 1 shows the existence of a 96% same directional and strong correlation between sovereign sukuk and Eurobond prices. Eurobond is an interest based and fixed income debt instrument that represents a loan made by an investor to a borrower, typically international governmental issuances. Due to its high correlation, and its similar characteristics with the sukuk data, the international dollar-based ten-year Eurobond (X_1) issued on 29.03.2014 was selected as the input. The second strongest relationship with sovereign sukuk prices was realized at -37% with the S&P MENA sukuk index. Since the sample sukuk data is an international issuance and Turkey is in the MENA region, the S&P MENA sukuk index (X_2) can be considered a benchmark of the international sukuk market. There is a 22%, 22% and 11% reverse correlation between the sovereign sukuk prices and the US Dollar Index (DXY), GPR, and the Chicago Board Options Exchange Volatility Index (VIX), indices, respectively.

The DXY index reflects the value of the dollar against the weighted geometric average of a basket of major currencies (Euro, British Pound, Canadian Dollar, Swedish Krona, Swiss Franc, and Japanese Yen). Since Eurobond and sovereign sukuk are issued in dollar currency, DXY index (X_3) is used to represent exchange rate risk in the study. To represent the global geopolitical risk, the GPR index (X_4), developed by Caldara & Iacoviello (2018), was selected as stated in Çetin's (2019) paper. Finally, the VIX index (X_5), which is determined to significantly affect the risk level of Islamic capital markets, is included in the study to represent the market risk (Hatipoğlu & Sekmen, 2018; Naifar, 2016).

Information on the variables used in the designed ANN model (Table 2) and data graphics (Fig. 1) are given below.

Table 2

Variables used in the designed ANN model

		Data	Explanation
INPUTS	X_1	Eurobond	*10-year USD treasury bond closing price
	X_2	S&P Sukuk	*S&PMENA sukuk index value
	X_3	DXY	*Dollar index value
	X_4	GPR	*Geopolitical risk index value
	X_5	VIX	*CBOE volatility index value
OUTPUT	Y	Sovereign Sukuk	*10-year USD sovereign sukuk closing price

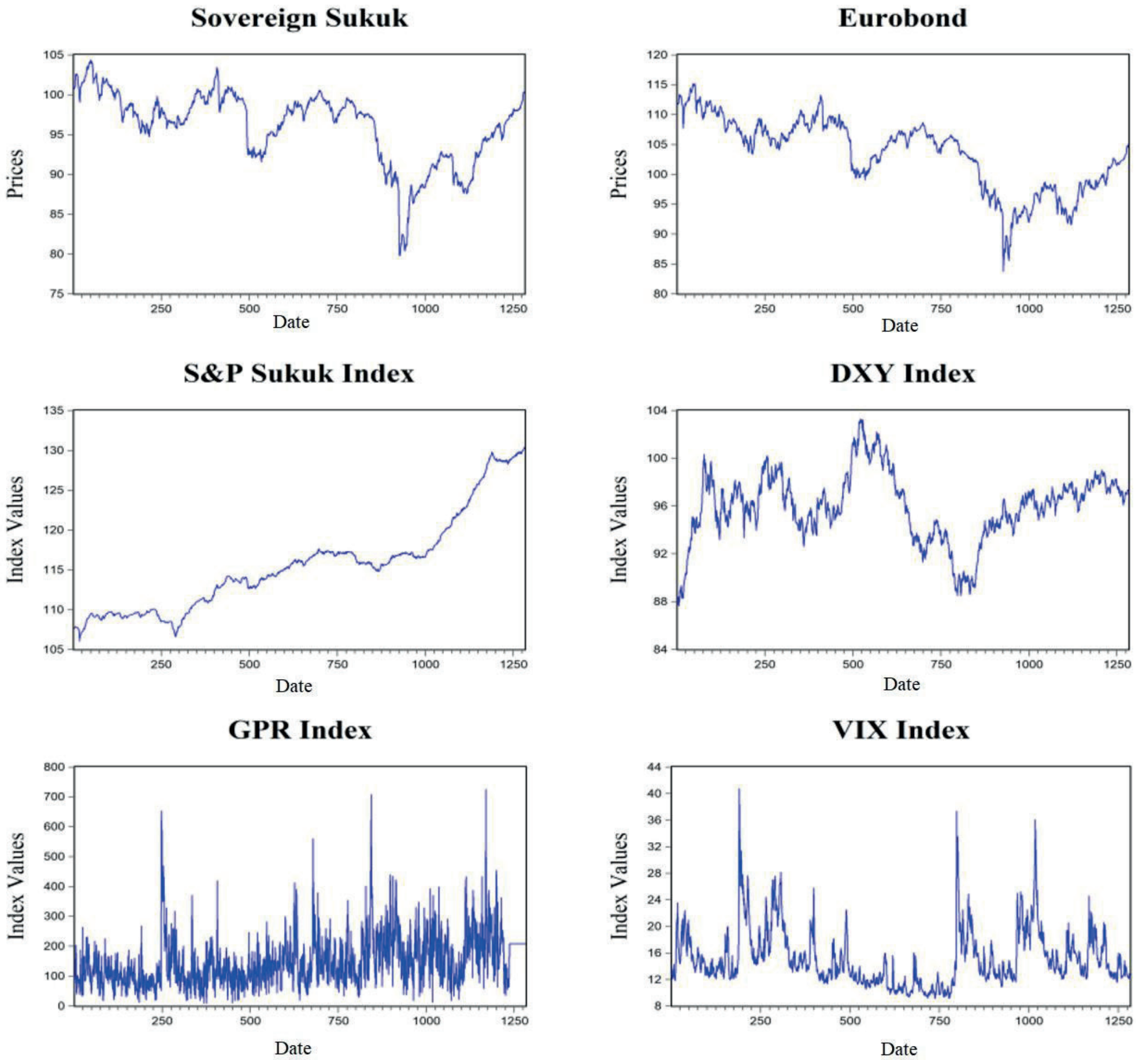


Figure 1. Data graphics for variables

4. MODEL

ANN was developed with inspiration from the human brain. It is a parallel and distributed information processing structure consisting of processing elements with its own memory. These processing elements are connected to each other by weighted connections. ANN can be defined as imitating biological neural networks with computer programs (Livingstone, 2008). Artificial nerve cells connect with each other, layers and layers come together to form a network structure. The structure of an ANN model is displayed in Fig. 2.

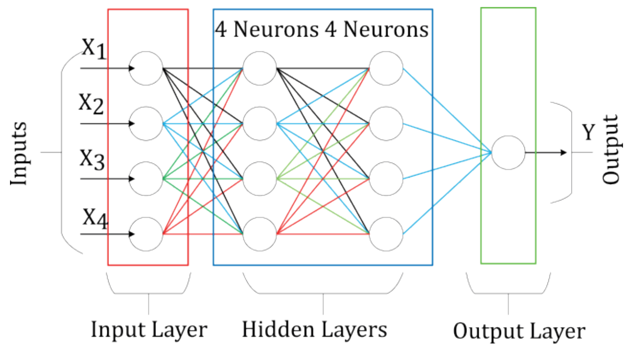


Figure 2. Artificial neural network structure

In Fig. 2, an artificial neural network structure consists of three main layers; input, hidden and output. The input layer consists of neurons that transmit data (inputs) from the external environment to the hidden layer. Input data are divided into training and testing sets, while training data is used for training the network; testing data are processed and used to determine the performance of the network on data that it has never seen (Livingstone, 2008).

4.1. Working Principle of an Artificial Neural Network

Data from the input layer is first summed by multiplying it with randomly determined weight values. An activation function is used to reduce the total value obtained at certain intervals. This process is repeated consecutively in the same way in all cells in the structure of the network. The output value of a cell in the hidden layer constitutes the input value of the cell after it. Finally, after repeating the same process, the output value of the system is created through the cells in the output layer (Mengi & Metlek, 2020).

Although the basic principles of ANN are as described above, there are also ANN models created with different connection types such as Adaline / Madaline, LVQ. In the study, the multi-layer feedforward neural network model was used.

4.2. Multi-Layer Feedforward Artificial Neural Network

Multi-Layer Feedforward (MLF) neural network is a dynamic model and generates successful results in nonlinear classification, curve fitting and prediction problems. The main logic of the model is that the error value of the network output is propagated backwards (Mengi & Metlek, 2020). Accordingly, it is also known as the back propagation algorithm in the literature.

First of all, the network should be run in the forward direction. In the forward direction of the network, Net function value is calculated by multiplying and summing the information coming from the input layer with the weight coefficients of the network as displayed in Equation 1. Depending on the architecture of the network, the bias value can also be added to the Net value as displayed by Equation 2.

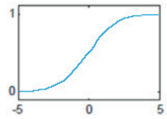
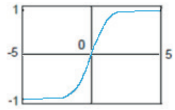
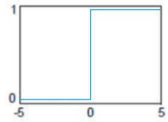
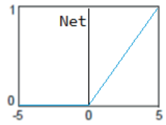
$$Net = \sum_{i=1}^{i=j} X_i W_i \tag{1}$$

$$Net = \sum_{i=1}^{i=j} X_i W_i + \beta w_i \tag{2}$$

The bias value is used to prevent the network from being attached to the global minimum or maximum points. In Equation 1,x_i denotes the ith input value and w_i denotes the weight value of the ith input. In Equation 2, β is the bias coefficient and w_i is the weight value of the bias.

Net value calculated with Equation 2 is transferred to one of the activation functions displayed in Table 3. Here, which activation function will be preferred depends on the data used and the researcher who designed the network.

Table 3
Activation functions

Sigmoid	$y = \frac{1}{1 + e^{-Net}}$		(3)
Hyperbolic Tangent	$y = \frac{e^{Net} - e^{-Net}}{e^{Net} + e^{-Net}}$		(4)
Step Function	$y = \begin{cases} 1 & Net \geq 0 \\ 0 & Net < 0 \end{cases}$		(5)
ReLu	$y = max\,(0, Net)$		(6)

Source: Metlek & Kayaalp, (2020).

The values resulting from the activation function of the cell can be a direct output of a network or output of a single cell, as displayed in Fig. 2. However, due to the multi-layered architecture used, the output of each cell in the hidden layer constitutes the input of another cell after it.

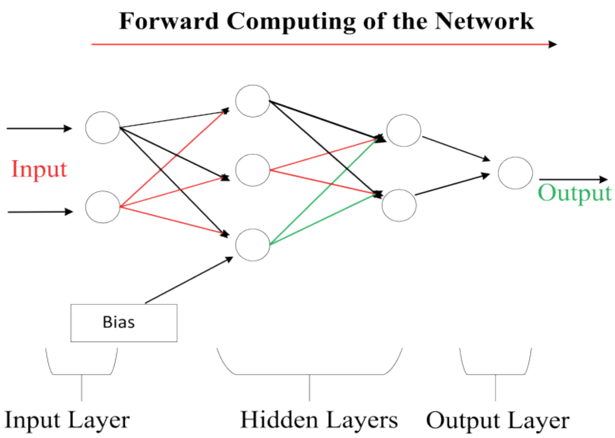


Figure 3. Forward computing of the network

Forward running of the network is continued up to the output layer. The weights of the all layers affect the output value of the system directly or indirectly. The value calculated in the output layer with the same method constitutes the output of the whole network.

4.2.1. Back Propagation Algorithm

The output value is compared with the expected value of the network. This comparison is made with Equation 7. The value obtained as a result of the comparison expresses the error of the system. A remarkable point is that weight values in all layers have an effect on this error value. Therefore, the error value obtained will propagate back step by step from the end to the beginning.

$$E(m) = Ex(m) - Out(m); \quad m = 1, \ldots, m \tag{7}$$

$$TE = \frac{1}{m}\sum_{1}^{M}\sqrt{E(m)^2} \tag{8}$$

$Ex(m)$ in Equations 7 and 8 indicates the expected value, $Out(m)$ denotes to the output of the system, and $E(m)$ denotes the error. If there is more than one output of the system, the total error TE can be examined with Equation 8.

Back propagation of the error from the output is executed in two stages. In the first step, the weights between the output and the hidden layer and in the second step, the weights between the input and the hidden layer are recalculated.

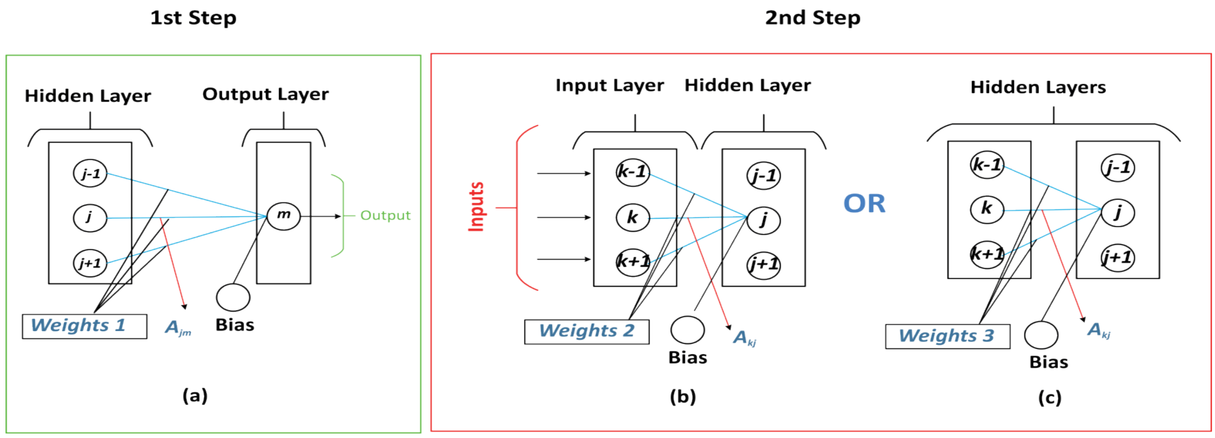


Figure 4. Updating (recalculation) the weights

Step 1: Updating the weights between the hidden and output layers

If the error of the output unit mth produced by the system in the tth iteration is called δ_m, firstly, calculating the value of δ_m with Equation 9 is required. Then, weights shown in Figure 4 (a), which connects the process element jth in the hidden layer to the mth process elements in the output layer, and the amount of change in ΔAa is calculated by Equation 10 (Mengi & Metlek, 2020).

$$\delta_m = f'(NET).E(m) \tag{9}$$

In equation 9, $f'(NET)$ denotes the derivative of the activation function.

$$\Delta A^{a}_{jm}(t) = \eta\delta_m Out^{a}_{j} + \alpha\Delta A^{a}_{jm}(t-1) \tag{10}$$

Equation 10 is used to calculate the amount of change in weights and it is expressed as ΔA^{A}. Concurrently, η denotes learning coefficient, α denotes momentum coefficient in Equation 10. The updated weights in tth iteration are calculated with Equation 11.

$$A^{a}_{jm}(t) = A^{a}_{jm}(t-1) + \Delta A^{a}_{jm}(T) \tag{11}$$

Similar to the weight values in the output layer displayed in Fig. 4(a), the bias value unit must be updated. If the bias value of mth cells in the output layer in tth iteration is expressed as β^{Out}_{m}, the change of the bias is calculated by Equation 12.

$$\Delta\beta^{Out}_{m}(t) = \eta\delta_m + \alpha\Delta\beta^{Out}_{m}(t-1) \tag{12}$$

With Equation 13, the new value of the bias is calculated.

$$\beta^{Out}_{m}(t) = \beta^{Out}_{m}(t-1) + \Delta\beta^{Out}_{m}(t) \tag{13}$$

Step 2: Update of weights between hidden and input layers or intra-hidden layers

As displayed in Figure 4. (b) and (c), the weights between the hidden and input layers or intra-hidden layers need to be updated in the second step. The reason for the errors in the output layer is the weights between the input and hidden layers as displayed in Fig. 4(b), or the weights of the intra-hidden layers displayed in Fig. 4(c).

The values of the output layer are obtained from the input and the intra-hidden layers. Accordingly, the error of the output layer is distributed to the hidden and input layers' weights (or intra-hidden layers) as shown in Fig. 4 (b) and (c). For this distribution process, the error donated by Δ^{A}_{j} A in Equation 14 is computed first.

$$\delta_j^a = f'(NET).\sum_{1}^{m}\delta_m A_{kj}^i \tag{14}$$

After calculating the error value, the amount of change in the weights indicated by Equation 15 and ΔA_{kj}^i is calculated.

$$\Delta A_{kj}^i(t) = \eta\delta_j^a Out_k^i + \alpha\Delta A_{kj}^i(t-1) \tag{15}$$

After calculating the amount of change in weights, the new weight values are computed with Equation 16.

$$\beta_j^a(t) = \beta_j^a(t-1) + \Delta\beta_j^a(t)$$

$$A_{kj}^i(t) = A_{kj}^i(t-1) + \Delta A_{kj}^i(t) \tag{16}$$

The bias is indicated with β^a In Fig. 4. (b) and (c), the change of the bias is calculated with Equation 17.

$$\Delta\beta_j^a(t) = \eta\beta_j^a + \alpha\Delta\beta_j^a(t-1) \tag{17}$$

Finally, the updated bias in the t[th] iteration is computed with Equation 18.

$$\beta_j^a(t) = \beta_j^a(t-1) + \Delta\beta_j^a(t) \tag{18}$$

All the weights will be updated by running the ANN working forward, and also backward. These processes will be repeated until the designed MLF model reaches the minimum error value or the iteration number. The consequence of the iterations of the network will be trained. After this process, the trained system will be tested and validated (Mengi & Metlek, 2020).

4.3. Error Functions

In the forecasting models, error functions are used to measure the performance of the model. The most commonly used error functions in the literature are Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Regression Determination Coefficient (R^2). MAE is the average of the difference between the estimated values of the model and the actual values, i.e., the absolute value of the error. MSE is the mean value of squares of errors; RMSE is the square root of MSE. MAPE is the mean percentage of the absolute values of the errors and R^2 refers to the regression determination coefficient. Error functions displayed in Equations 19, 20, 21, 22, and 23 were used to measure the success of the forecasted values obtained from the output of the designed model, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{actual\_i} - Y_{forecasted\_i}\right| \tag{19}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{forecasted\_i}\right)^2 \tag{20}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{forecasted\_i}\right)^2} = \sqrt{MSE} \tag{21}$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_{actual\_i} - Y_{forecasted\_i}\right|}{\left|Y_{actual\_i}\right|}\right) * 100 \tag{22}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{actual} - Y_{forecasted\_i}\right)^2}{\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{actual\_mean\_i}\right)^2} \tag{23}$$

5. EXPERIMENTAL STUDY

The input layer of the designed model consists of Turkish Treasury Eurobond closing prices (X_1), S&P MENA sukuk index (X_2), DXY index (X_3), GPR index (X_4), and VIX index (X_5), and the output layer consists of Turkish sovereign sukuk closing prices (Y). In the model, 1282 daily data were used.

In order to train the model, the input data set is divided into the splits according to the k-fold 5 cross-validations as 80% of data as training, 10% as testing and 10% as verification subsets. Thus, 1025 of 1282 data were used for training, 128 for testing and 128 for verification. Two data were excluded from analysis due to residual split. 0.01 error value or 1000 iteration condition has been determined to end the training process of the system. The ANN model was designed using the Matrix Laboratory (MATLAB) - R2020a program.

Considering the characteristics of the data set, multi-layer feedforward neural network architecture has been chosen. Since there is no general rule in creating the network architecture in ANN model, the best performance network structure was determined by creating ten models with different features. The model with the best performance was chosen according to the least mean square error (MSE) value. The trial test results are displayed in Table 4.

Table 4

Network architecture trial results

Model	Features	1st Hidden Layer	2nd Hidden Layer	3rd Hidden Layer	4th Hidden Layer	R	MSE
M_1	Number of Neurons	12	-	-	-	0,9856	0,4465
	Activation Function	Tansig					
M_2	Number of Neurons	6	4	-	-	0,9835	0,4239
	Activation Function	Purelin	Radbas				
M3	**Number of Neurons**	**10**	**8**	**-**	**-**	**0,9979**	**0,1292**
	Activation Function	**Tansig**	**Tansig**				
M_4	Number of Neurons	16	14	-	-	0,9871	0,4865
	Activation Function	Radbas	Radbas				
M_5	Number of Neurons	4	2	2	-	0,9938	0,2945
	Activation Function	Logsig	Purelin	Radbas			
M_6	Number of Neurons	14	12	10	-	0,9881	0,4947
	Activation Function	Purelin	Purelin	Purelin			
M_7	Number of Neurons	16	14	12	-	0,9896	0,3289
	Activation Function	Radbas	Radbas	Radbas			
M_8	Number of Neurons	6	4	3	2	0,9899	0,4348
	Activation Function	Purelin	Radbas	Purelin	Logsig		
M_9	Number of Neurons	14	12	10	6	0,9864	0,4645
	Activation Function	Purelin	Purelin	Purelin	Logsig		
M_{10}	Number of Neurons	18	16	14	10	0,9861	0,4308
	Activation Function	Tansig	Tansig	Logsig	Logsig		

The features of the M_3 model, which has the best forecasting performance as a result of the trials, are presented in Table 5.

Table 5

Features of the designed MLF model

Features	Number of Neurons / Values	Activation Functions
Input Layer	5	
1st Hidden Layer	10	Hyperbolic Tangent and Sigmoid Functions
2nd Hidden Layer	8	Hyperbolic Tangent and Sigmoid Functions
Output Layer	1	
Network Structure	Feedforward - Back Propagation Algorithm	
Number of Iteration	1.000	

ANN performance is measured in terms of error minimization and regression fit of data sets. The regression (R) value is an indicator of the relationship between predicted output values and target values. For R = 1, there is an exact relationship between predicted output and known target values, and almost all sample data points fit the hyper-level obtained by regression.

Fig. 5 shows regression graphs for training, validation, testing, and all data. The dashed line on each graph represents the perfect result where the outputs of the model are equal to the target values (Y = T), that is, the forecasted values to the actual values. A solid line with different colours represents the optimal linear regression fit between outputs and targets. The R values for training, validation, testing and all data sets were 99.84%, 99.67%, 99.59%, and 99.79%, respectively. It is seen that all points are located on the regression line that states strong correlation between the sukuk prices forecasted by the designed MLF model and actual sovereign sukuk prices.

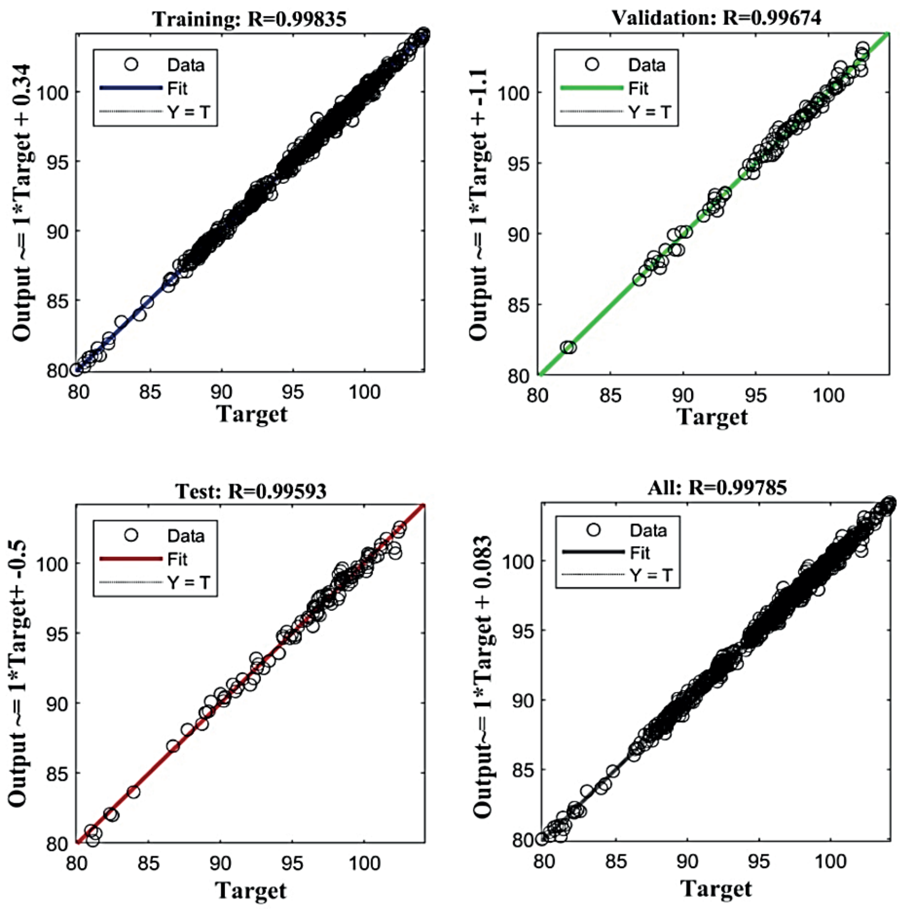


Figure 5. Regression analysis results

In order to validate the forecasting performance of the model, MAE, MSE, RMSE, MAPE, and R^2 values were calculated by applying the error functions given in Equations 19, 20, 21, 22, and 23. Performance results are displayed in Table 6.

Table 6

Performance results

Error Function	Error Value / Rate
MAE	0,2661
MSE	0,1292
RMSE	0,3594
MAPE	0,0028
R^2	0,9957

In the table, the error values of the model are quite low as the mean absolute percent error (MAPE) is 0.28%. In the literature, the forecasting performance of models with a MAPE value less than 10% is grouped as "very good" (Yakut et al., 2014). Since the MAPE value of the designed model is realized well below 10%, it can be said that the forecasting performance of the model is quite good.

The graph images the forecasted and actual sovereign sukuk closing prices in Fig. 6.

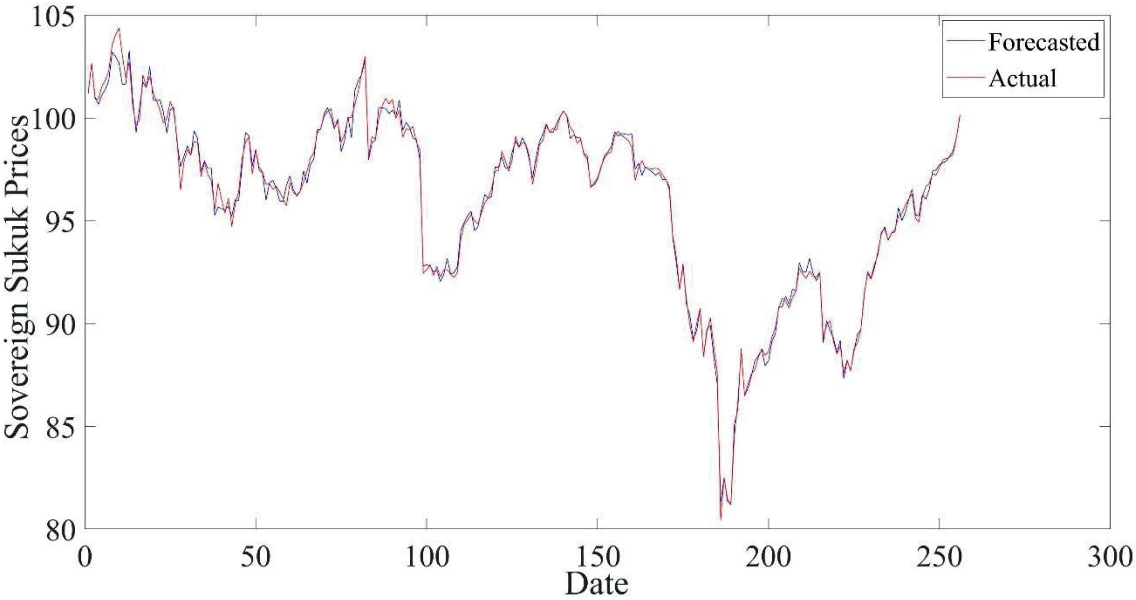


Figure 6. Graph of forecasted and actual sovereign sukuk prices

In the graph, the curve expressed with the red line denotes the actual sukuk prices, whereas the curve expressed with the blue line denotes the forecasted sukuk prices. When the graph is examined, it is observed that the curves are in great harmony with each other. This indicates that the designed MLF model and the selected inputs perform high success in forecasting the sovereign sukuk prices.

6. CONCLUSION

Sukuk are securities that entitle the investor to receive a share of the income or profit in order to meet financing needs according to Islamic principles in capital markets. Over the last decade, they have become one of the most attractive Sharia-compliant investment products worldwide. Despite the increasing interest, the fact that the price forecasting studies on sukuk are extremely scarce has been the main motivation of this study. In the study, to forecast the price of sovereign sukuk in Turkey, the ANN model was used and MLF neural network model was designed.

Four of the input variables (DXY, VIX, GPR, S&P MENA sukuk) are data used on an index basis. Index-based data gives the power to represent a large amount of data with a single value. This increases the forecasting power of input variables of the sukuk prices. Besides, the designed network architecture has a significant effect on the forecasting performance. In order to determine the most appropriate network architecture, ten models with different layers, neuron numbers, and activation functions were designed and the model providing the lowest error value was selected. The two-hidden layer feedforward network of ten and eight neurons using tangent hyperbolic activation functions was the model with the best success performance in forecasting sukuk prices.

Findings reveal that the designed model accurately forecasts the dollar-based international sovereign sukuk prices with an error margin of 2.8 per thousand, and with 99.98% success rate, according to the MAPE error function. The success rate of the model is far above the 94% success rate achieved in the study of Yigiter et al., (2018) forecasted corporate sukuk prices with the K-NN model, and the 80% success rate achieved in the study of Wardani et al., (2020) forecasted R&D sukuk returns with binomial decision tree model.

The very high forecasting success rate in ANN models requires an assessment of the probability that the network may have memorized. In the designed model, cross validation was applied by splitting the dataset according to the k-fold 5 value, thus avoiding the possibility of memorizing the network. The high forecasting performance of the network should be attributed to the success in the selection of input variables and the suitability of the designed network architecture to the data.

In sukuk markets, high uncertainty caused by factors such as geopolitical risk, exchange rate and interest rate risk can be minimized through the ANN model. By virtue of the designed model, investors will be able to forecast the sukuk prices they want to invest accurately and make their trading decisions accordingly. Successful price forecasts in economic turbulence terms will reduce the risk perception of sukuk investors and increase their profitability. Thus, it will be possible for more investors to trade in the sukuk market and to gain depth in the sukuk's secondary market.

The result of the study is important in that it proves that the ANN model is an effective model for forecasting sukuk prices and that the DXY, VIX, GPR, S&P MENA sukuk indices and Eurobond bond prices are determinants. Since this paper is the first study in Turkey to forecast sukuk prices with the ANN model, it can serve as a reference for the future works. The designed MLF model and determined input variables can be applied to all dollar-based international sovereign sukuk to be issued in the future. In addition, the ANN model can be used in forecasting sukuk prices indexed to gold, Consumer Price Index, and Turkish Lira issued by the government and corporations.

Peer-review: Externally peer-reviewed.
Conflict of Interest: The authors have no conflict of interest to declare.
Author Contributions: Conception/Design of Study- D.T.Ç., S.M.; Data Acquisition-M.C.Y.; Data Analysis/Interpretation- D.T.Ç., S.M.; Drafting Manuscript- D.T.Ç., S.M.; Critical Revision of Manuscript- D.T.Ç., S.M.; Final Approval and Accountability- D.T.Ç., S.M.
Grant Support: The authors declared that this study has received no financial support.

Hakem Değerlendirmesi: Dış bağımsız.
Çıkar Çatışması: Yazarlar çıkar çatışması bildirmemiştir.
Yazar Katkıları: Çalışma Konsepti/Tasarım-D.T.Ç., S.M.; Veri Toplama-M.C.Y.; Veri Analizi/Yorumlama- D.T.Ç., S.M.; Yazı Taslağı- D.T.Ç., S.M.; İçeriğin Eleştirel İncelemesi- D.T.Ç., S.M.; Son Onay ve Sorumluluk- D.T.Ç., S.M.
Finansal Destek: Yazarlar bu çalışma için finansal destek almadığını beyan etmiştir.

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