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GREEN BONDS IN CLIMATE FINANCE AND FORECASTING OF CORPORATE GREEN BOND INDEX VALUE WITH ARTIFICIAL INTELLIGENCE*

İKLİM FİNANSMANINDA YEŞİL TAHVİLLER VE YAPAY ZEKÂ İLE KURUMSAL YEŞİL TAHVİL ENDEKS DEĞERİNİN TAHMİNİ

Dilşad Tülgen ÇETİN**

Abstract

The effects of global climate change and increasing environmental awareness have led to an increase in the significance of climate projects and, accordingly, climate finance and green bonds. Despite the increasing significance, the fact that the price or index value forecasting studies on green bonds are extremely scarce has been the main motivation of this study. The aim of the paper is to forecast the corporate green bond index value with the Artificial Neural Network model and to determine the predictor by addressing the conceptual framework of green bonds. For this purpose, the Multi-Layer Feedback Artificial Neural Network (MLF-ANN) model, in which S&P 500 bond index values are determined as input and S&P green bond index values as output, is designed. To determine whether the conventional bond index values are the predictor of the corporate green bond index, the S&P 500 bond index were used as the sole input of the forecasting model. The findings show that S&P green bond index values are forecasted with 1.13% Mean Absolute Percentage Error (MAPE) and 98.93% Regression Determination Coefficient (R^2). The results of the research provide data to maximize profits and/or minimize risk for green bond investors and market makers, while providing insight into the effectiveness of green bonds in financing climate projects for policy makers. This paper is the first study in the literature in terms of proving the effectiveness of the MLF-ANN model in forecasting corporate green bond index value and revealing that conventional bond index is the predictor of the model. Thus, it is expected that the study will shed light on future studies.

Keywords: Green bonds forecasting, Artificial Neural Network model, Predictor of green bonds, Conventional bonds.

JEL Classification: G17, C63, Q56.

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Öz

Küresel iklim değişikliğinin etkileri ve artan çevre bilinci, iklim projelerinin ve buna bağlı olarak iklim finansmanı ve yeşil tahvillerin öneminin artmasına yol açmıştır. Artan önemine karşın yeşil tahvillere ilişkin fiyat veya endeks değeri tahmin çalışmalarının son derece az olması, bu çalışmanın temel motivasyonunu oluşturmuştur. Bu makalenin amacı, yeşil tahvillerin kavramsal çerçevesini ele alarak kurumsal yeşil tahvil endeks değerini Yapay Sinir Ağı modeli ile tahmin etmek ve tahmin ediciyi belirlemektir. Bu amaçla, girdi olarak S&P 500 tahvil endeks değerlerinin ve çıktı olarak S&P yeşil tahvil endeks değerlerinin belirlendiği Çok Katmanlı Geri Beslemeli Yapay Sinir Ağı modeli tasarlanmıştır. Konvansiyonel tahvil endeks değerinin kurumsal yeşil tahvil endeksinin tahmincisi olup olmadığını belirlemek için tahmin modelinin tek girdisi olarak S&P 500 tahvil endeksi kullanılmıştır. Bulgular, S&P yeşil tahvil endeks değerinin %1,13 Ortalama Mutlak Yüzde Hatası (MAPE) ve %98,93 Regresyon Belirleme Katsayısı (R^2) ile tahmin edildiğini göstermektedir. Araştırmanın sonuçları, yeşil tahvil yatırımcıları ve piyasa yapıcıları için kârı en üst düzeye çıkarmak ve/veya riski en aza indirmek için veriler sağlarken, politika yapıcılar için iklim projelerini finanse etmede yeşil tahvillerin etkinliğine ilişkin iç görü sağlamaktadır. Bu makale, MLF-ANN modelinin kurumsal yeşil tahvil endeks değerinin tahmininde etkinliğini kanıtlaması ve konvansiyonel tahvil endeks değerinin modelin tahmincisi olduğunu ortaya koyması açısından literatürdeki ilk çalışmadır. Bu nedenle çalışmanın ileride yapılacak araştırmalara ışık tutması umulmaktadır.

Anahtar Kelimeler: Yeşil tahvil tahmini, Yapay Sinir Ağı modeli, Yeşil tahvillerin tahmincisi, Konvansiyonel tahviller.

JEL Sınıflandırılması: G17, C63, Q56.

1. Introduction

The threat of climate change has revealed that a global effort is needed to take the necessary measures in the world. In 2015, through the Paris Agreement, the United Nations made a universal call to reduce global temperature rise to 2°C below established pre-industrial levels (UNFCCC, 2021). Following the elaboration of the United Nations Framework Convention on Climate Change (UNFCCC) agenda, governments around the world have come up with their own strategies for tackling climate change issues for a greener future. However, the implementation of these strategies will incur an enormous financial cost.

Climate projects are investments that countries must undertake to turn the world economy onto a low-carbon path, reduce greenhouse gas concentration levels, and increase resilience to climate change. The fact that green projects have higher capital requirements, higher risk perception, and longer investment timelines than their alternatives, restricts private investments in climate projects (OECD, 2017). At this point, it is significant to encourage and support the private sector to invest in green projects.

Climate finance is the financing of environmentally friendly projects to mitigate climate change and environmental pollution by providing appropriate opportunities by government and/or financial institutions. In climate finance, green bonds, an interest-based financial instrument, and green Sukuk, an interest-free Islamic financial instrument, are issued as capital market instruments (Hong et al., 2020).

Green bonds, first issued in 2007, are a capital market instrument in which proceeds are invested only in climate or environmentally friendly green projects. With the increasing sensitivity of countries to environmental issues, the significance of the green bond market is increasing day by day. This makes the forecasting of green bond index values, even more, significant in order to reduce uncertainty for investors and market makers in the market.

This study has two significant purposes. The primary purpose is to forecast the corporate green bond index values with the Artificial Neural Network (ANN) model. The secondary purpose is to determine whether the conventional bond index values are the predictor of the corporate green bond index values. For this purpose, a Multilayer Feedback Artificial Neural Network (MLF-ANN) model is designed in which S&P 500 bond index values are determined as input and S&P green bond index values as output.

The research will contribute to the literature by shedding light on future works on the forecasting of green bond index values, where there are limited eligible studies. The accurate predictability of the green bond index will play an active role in reducing the risk perception of investors and increasing their profitability.

The paper consists of five sections. In the second section, there is a literature review on green bonds and their markets. In the third section, the dataset and methodology of the research are given. In the fourth section, the research findings are presented. Finally, in the fifth section, the conclusions of the study are discussed.

2. Literature Review

2.1. Green Bonds

The bond market has the potential to close the financing gap of climate and environmentally friendly projects by mobilizing debt financing from a wider investor base than banks. In 2007, the World Bank introduced green bonds, also called climate bonds, to meet the increasing demand for investment opportunities that include environmental, social and governance criteria and have a sustainable impact.

Green bonds are a type of bond that provides financing for green projects, integrating the trust element of fixed income vehicles with the awareness of adapting to the climate. It has the similar features as conventional bonds in terms of yield, maturity and validation, but has some additional obligations regarding the use of funds and proceeds (Çetin, 2021). Proceeds of green bonds can only be used in green project investments such as, renewable energy generation and transmission projects, investments to increase energy efficiency, projects aimed at preventing or reducing pollution, investments for the sustainability of natural life, investments in sustainable water resources management, investments for clean transportation and reducing carbon emissions (ICMA, 2018). It provides competitive cost advantages to their issuers due to the government subsidies, tax exemptions, low interest rates and low issuance costs, etc. (Ehlers & Packer, 2017).

Green bonds are divided into two types as labeled and unlabeled green bonds. Labeled green bonds are the bonds which proceeds are promised to be used in green projects and monitored in sub-accounts accordingly. Unlabeled green bonds meet certain criteria, such as investing in projects with low CO2 emissions, but proceeds are not tracked in sub-accounts and do not directly finance green projects (CBI, 2016).

Green bonds offer several benefits for both investors and issuers, such: (i) low interest rates and issuance costs, (ii) high long-term financing, (iii) transparency in the use of resources, (iv) increasing the reputation of the issuer and climate awareness of investors, and (v) supporting government-private partnerships. Along with the advantages of green bonds, there are also some disadvantages such as (i) lack of standardization, (ii) insufficient transparency in reporting, (iii) additional costs of reporting and monitoring, (iv) low market depth and liquidity, (v) insufficient investor sentiment (Çetin, 2021).

2.2. Global Green Bond Market

The first green bond was issued in 2007 by the European Investment Bank with an amount of 600 million Euros to finance renewable energy and energy efficiency projects (Ehlers & Packer, 2017). In the green bond market, a total of 776.4 billion dollars was issued in period of 2007-2019. Annual green bond issuance is estimated to potentially reach a trillion dollar in the 2020s (CBI, 2020). Distribution of green bond issuance by regions is presented in Table 1 (CBI, 2020).

Table 1: Green Bond Issuance by Regions (2007-2019)

Region	Countries	Issuers	Amount (Billion USD)
Europe	25	269	307.4
North America	2	167	190.4
Asia-Pacific	18	345	183.6
Transnational		11	79.4
Latin America	11	47	12.9
Africa	6	16	2.7
Total	62	855	776.4

Source: CBI. (2020).

In Table 1, European countries rank first with green sukuk issuance of 307.4 billion dollars, followed by the issuance of America and Canada (North America) with 190.4 billion dollars. The green bond market reached a volume of $245.8 billion as of the end of 2019 and 71.2% of the market volume is realized by the top ten countries in the ranking. The top ten countries in green bond issuance in 2019 are given in Table 2.

Table 2: Top 10 Countries in Green Bond Issuance (2019)

Countries	Issuers	Issuances	Amount (Billion USD)
USA	105	1128	51.3
China	79	99	31.3
France	19	54	30.1
Germany	12	25	18.7
Holland	15	17	15.1
Sweden	40	106	10.3
Japan	47	66	7.2
Canada	14	17	7
Italy	10	11	6.8
Spain	11	17	6.5
Total	352	1540	184.3

Source: CBI. (2020).

In Table 2, USA is the leader with 51.3 billion dollars issuance and 19.8% share in the green bond market, followed by China with 12% and France with 11.6%.

The usage areas of the proceeds generated by the green bond issuance are shown in Figure 1.

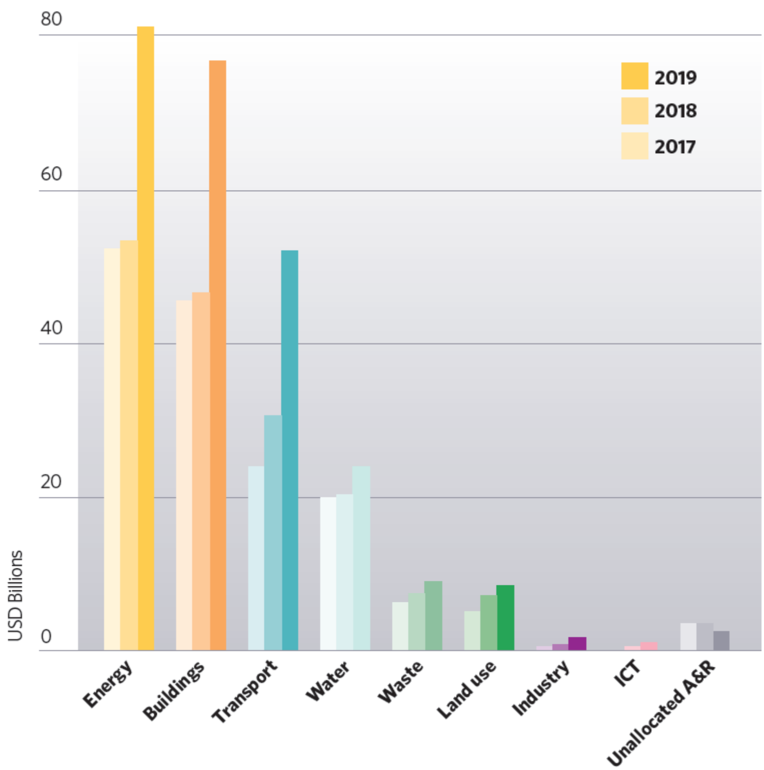

Figure 1: Use of Proceeds Categories of Green Bonds (2017-2019)

Source: CBI. (2020).

In Figure 1, in 2019, green bond proceeds were used in energy investments (32%), buildings (30%), transportation (20%), water (9%), waste (3%), land use (3%), industry (1%), informatics (1%) and unallocated A&R (1%), respectively.

In Turkey, the first unlabeled green bond was issued in 2016 by the Turkish Industrial Development Bank. Only five issuances worth 5.28 billion TL have been made since 2016. Labeled bond issuance has not been realized yet. Although the green bond market in Turkey has not grown much, it is a market that has the potential to grow in the future with the increase in environmental awareness of the investors and issuers (Çetin, 2021).

2.3. Related Studies

In the literature, it is seen that many academic studies have been conducted on the use of artificial neural networks in economics and finance (Guan et al., 2018; Kamalov, 2020; Sigo, 2018). Despite the massive literature in this area, there are fewer scientific studies on yield prediction in fixed-income bond markets (Almeida et al., 2018; Nunes et al., 2019b; Wegener et al., 2016). Although the significance of bond markets for national economies is quite large, one of the main reasons for this situation is that bond yields are a single-target regression problem. However, in some artificial intelligence-based studies conducted in recent years, it is seen that models related to the forecasting of the yield curve have been made. Forecasting the yield curve is a much more complex problem than predicting the bond yield because the target of the model is not a single value but a curve (Hyndman, 2021; Nunes et al., 2018, 2019a).

Although mitigating the effects of climate change is of critical significance for our world, the green bond market has not developed enough yet. Since green bonds are a much newer asset class compared to the conventional bond market, there are much less academic studies based on artificial intelligence, although they are becoming more popular (Debrah et al., 2022; Fang et al., 2021; Feng et al., 2021). While this clearly represents an opportunity for our study, it is also one of the challenges of this research.

We can say that the majority of academic studies on green bonds focus on understanding the conceptual framework and discussing its applicability (Açar, 2021; Baysan, 2019; Deschryver & De Mariz, 2020; Diriöz, 2021; Kandır & Yakar, 2017a, 2017b; Turguttopbaş, 2020; Zerbib, 2017). In order for green bonds to be considered as an investment tool for countries to achieve their sustainable development goals, governments should provide incentives such as subsidies, tax breaks, discount systems, and other concessions to make green bonds attractive (Kapoor et al., 2020).

On the other hand, when green bonds are compared with their closest counterparts, the "brown" bonds, in terms of yield, volatility, and liquidity, it was also a matter of curiosity whether there was an occasional green premium or greenium (Löffler et al., 2021). Zerbib, (2017) showed a mostly negative green bond premium, claiming that the rating and the amount issued are the main drivers of the premium. Contrary to Zerbib's (2017) study results, Karpf & Mandel (2018) showed that the green premium is positive in the green bond issued by the US municipal bond market.

Febi et al., (2018) argues that the liquidity risk for green bonds is negligible, while Reboredo, (2018) found that green bond yields are strongly correlated with corporate and sovereign bond yields, whereas they move weakly with stocks and energy commodities. Baker, et. all, (2018) on the other hand, compared green bonds with conventional ones in terms of yield profile. They examined more than 2,000 samples of municipal and corporate green bonds and found that green bonds traded with lower yields (approx. 6 basis points) than bonds with similar characteristics.

Tang & Zhang, (2020) investigated the effect of green bond issuances of companies on the stock prices of the same company and obtained striking results. They revealed that the issuance of green bonds positively affects the stock prices of the company and increases its liquidity.

In terms of volatility, labeled green bonds are more volatile than unlabeled ones, (Pham, 2016), and compared to stock market volatility, they are more sensitive to positive shocks than negative ones, (Park et al., 2020). Also found that portfolios including green bonds provide much better risk-return than conventional bonds for diversification (Han et al., 2020).

One of the issues that will play a significant role in the design of this research is to reveal the determinants of green bond index values. It is especially critical for modeling the correlation between the green bond and the traditional bond markets. At this point, the work of Broadstock & Cheng, (2019) is remarkable. The authors considered the main determinants of the correlation models between the green and conventional (black) bond markets in their studies, as VIX (Chicago Board Options Exchange volatility index), ADS (The economic activity index developed by Aruoba et al., 2009), EPU (Economic policy uncertainty index developed by Baker et al., 2016), and oil prices (taken from the US Energy Information Administration) analyzed with dynamic conditional correlations (DCC) model developed by Engle, (2002). The results of the study, in which Standard and Poor's indices were used as the dataset, proved that the connection between green and black bonds was sensitive to the determinants selected in the research, as well as proving the strong relationship between these. Similarly, Reboredo et al., (2020) and Reboredo & Ugolini, (2020) investigated the price connectedness between green bonds and financial markets using the VAR model and found that there were strong price spreads between green bond markets and treasury and foreign exchange markets.

Although conventional bond index values were chosen as determinants in the artificial neural network model designed to forecast S&P green bond index values in this study, the determinants revealed by the researches of Broadstock & Cheng, (2019), Reboredo & Ugolini, (2020) and Reboredo et al., (2020) provides strong evidence for inclusion in the ANN model in future studies.

Though these studies analyze green bond markets on different issues; none of them forecast green bond prices or index values. The only forecasting study available is the research of Ngwakwe, (2021) and he forecasted green bond index values with 0.7668 Regression Determination Coefficient (R^2) and 1.3189 Mean Absolute Percentage Error (MAPE) values using the linear regression model.

Despite the limited number of studies on green bond markets, there is a massive literature on the forecasting of financial asset prices with Artificial Neural Networks (ANN). Studies prove that ANN can predict financial asset prices or values with high accuracy (Tealab et al., 2017) and its prediction performance is superior to linear models (Ma, 2020; Maheswari et al., 2021).

3. Material and Method

In the research, Multilayer Feedback Artificial Neural Network (MLF-ANN) model was preferred due to its success in forecasting financial time series (Bahrammirzaee, 2010; Ismail et al., 2018; Maheswari et al., 2021).

3.1. Dataset

The forecasting performance of an artificial intelligence method depends on clearly stating the problem and modeling the nonlinear complex relationship between input and output variables appropriately. In particular, the determination of input variables is significant as it directly affects the success of the model.

There are several studies in the literature that reveal the relationship between conventional and green bonds (Hachenberg & Schiereck, 2018). Based on these studies, the S&P 500 Bond Index was determined as the only input variable of the model. The reason for using a single input in the research is to reveal whether the conventional bond index values are the determinant of the green bond index value forecasting.

In the research, S&P 500 Bond Index daily values are used as input and S&P green bond index daily values are used as output for the data period of 31.05.2011-01.06.2021. In the study, the last 5-day average of the S&P 500 Bond Index values (calculated with Equation 1) used as the input variable was used in order to increase the forecasting performance of the input variable and to prevent the sudden increases and decreases in the index value from negatively affecting the training of the network.

$$\sum_{i=1}^{5} X_{(t-i)/5} \tag{1}$$

In Equation 1, *t* represents the time (day) of the variable Y to be forecasted and *i* denote the number of days back from that *t* time. Thus, the S&P Green Bond Index value (Y_t) at time *t* to be forecasted with the last 5 days average value of $X_{\bar{t}}$ starting from (t-1) to (t-5).

The characteristics of the S&P green bond index are presented in Table 3.

Table 3: S&P Green Bond Index Characteristics

Characteristics	S&P Green Bond Index
Weighting Method	Market value weighted
Calculation Currencies	USD
First Value Date	Nov 28, 2008
Launch Date	Jul 31, 2014
Number of Constituents	9,953
Total Par Value (USD Millions)	992,237.40
Market Value Outstanding (USD Millions)	1,050,867.80
Par Weighted Coupon	1.75%
Weighted Average Maturity	11.23 Years
Par Weighted Price	105.29
Yield To Maturity	0.96%
Yield To Worst	0.85%

The time series plots of the variables used in the ANN model are presented in Figure 2.

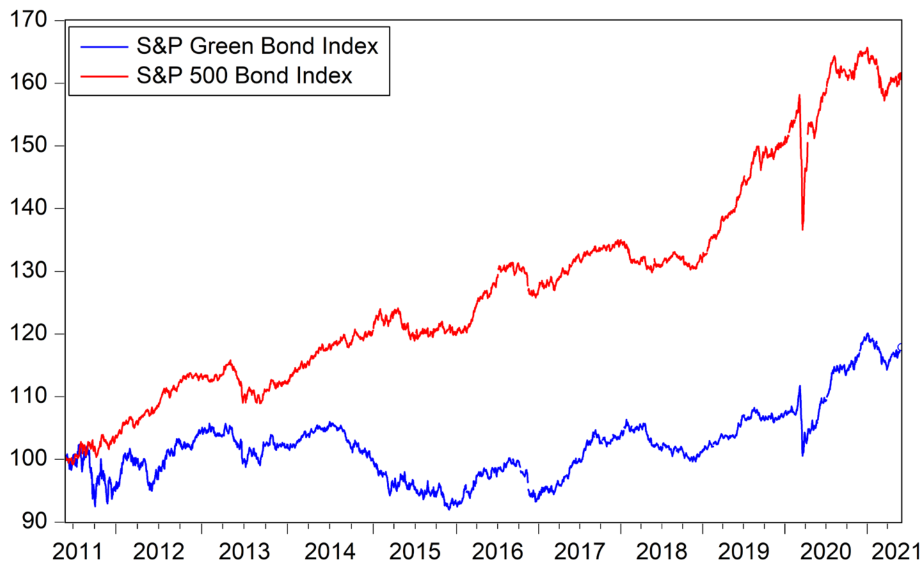

Figure 2: S&P Green Bond –S&P 500 Bond Indices Time Series Plots (31th May, 2011-1st June, 2021)

In Figure 2, the tendency to move together between both variables is clearly seen. The existence of this tendency is also confirmed by the correlation analysis result in Table 4.

Table 4: Correlation Analysis of Variables

	S&P Green Bond Index	S&P 500 Bond Index
S&P Green Bond Index	1	0.704851

The correlation between the series is quite high with %70.48. The correlation result provides preliminary evidence that the S&P 500 bond index can be the predictor of the S&P green bond index. S&P 500 bond index and S&P green bond index daily data were normalized and used in the training and testing stages of the designed ANN model.

3.2. Model

ANN, developed with inspiration from the human brain, interconnected by weighted links, composed of processing elements with their own memory, is parallel and distributed computing structure. It consists of three main layers: input, hidden and output layers. The structure of the ANN is displayed in Figure 3.

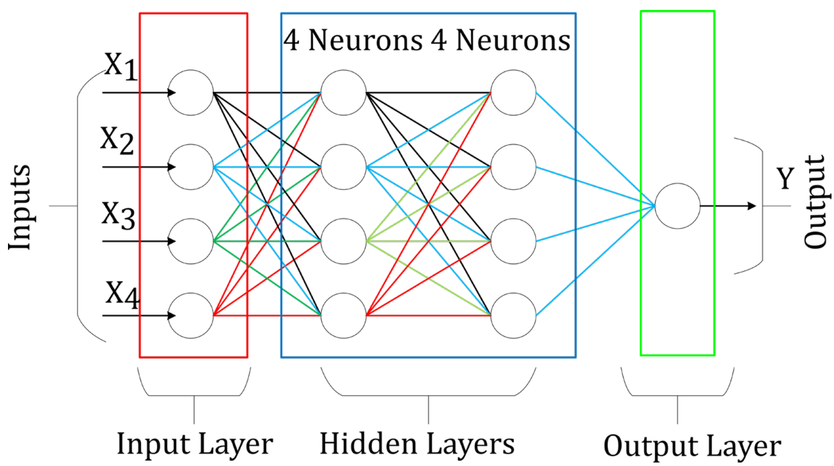

Figure 3: Artificial Neural Network Structure

MLF-ANN model is based on the principle of updating the weights of and propagating the error obtained from the output of the network, from the output layer to the input layer (Mengi & Metlek, 2020). The data presented to the input layer is split into two groups as training and testing. First, the model is run forward. Net value for the data coming to the input layer is calculated by Equation 2 and accordingly the bias value is calculated by Equation 3 to be added to Net value.

$$\text{Net} = \sum_{i=1}^{i=j} X_i W_i \tag{2}$$

$$\text{Net} = \sum_{i=1}^{i=j} X_i W_i + \beta w_i \tag{3}$$

In Equation 2, x_i indicates the ith input value and w_i indicates the weight value of the ith input. In Equation 3, β is the bias coefficient and w_i is the weight value of the bias.

In the hidden layer, the data is processed with the activation function. In the research the hyperbolic tangent (in Equation 4) and sigmoid (in Equation 5) functions are used as activation functions of the network.

$$y = \frac{e^{Net} - e^{-Net}}{e^{Net} + e^{-Net}} \tag{4}$$

$$y = \frac{1}{1 + e^{-Net}} \tag{5}$$

The model continues to run forward until the output value is generated in the output layer. At the end, the error value is calculated by comparing the output value with the target value as formulated in Equation 6 and the error distributed backward with the back propagation algorithm.

$$\text{Error(M)} = \text{Target(M)} - \text{Output(M)}; \quad \text{m} = 1, .., \text{m} \tag{6}$$

This process is repeated until the number of iterations or target error rate is reached and finally, the output value of the system is generated.

In prediction models, error functions are used to measure the forecasting performance of the model. The most commonly used error functions in the literature are Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Regression Determination Coefficient (R^2) and they formulated in Equation 7-11.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| Y_{actual\_i} - Y_{forecasted\_i} \right| \tag{7}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{forecasted\_i}\right)^2 \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{forecasted\_i}\right)^2} = \sqrt{MSE} \tag{9}$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_{actual\_i} - Y_{forecasted\_i}\right|}{\left|Y_{actual\_i}\right|}\right) * 100 \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{actual} - Y_{forecasted\_i}\right)^2}{\sum_{i=1}^{n}\left(Y_{actual\_i} - Y_{actual\_mean\_i}\right)^2} \tag{11}$$

3.3. Research Design

In the research, S&P 500 bond index was used as an input parameter and S&P green bond index as the output parameter for the daily data period of 31.05.2011-01.06.2021. A total of 2545 days of data were obtained and split into two as training (80%) and testing (20%) according to the K-Fold 5 cross-validation. The designed model was developed in MATLAB – R2020a.

Many tests were performed to determine the optimum parameters in the MLF – ANN model used in the study. The tested value ranges and the optimum values obtained are presented in detail in Table 5. These value ranges are frequently used in the literature and are also the main assumptions of the study (Mengi & Metlek, 2020). The designed model is visualized in Figure 4.w

Table 5: Features of the Designed MLF-ANN Model

	Features	Tested Range	Number of Neurons
Input Layer	Input	1	1
Hidden Layer	1st Hidden Layer	1-250	100
	1st Hidden Layer Activation Functions	Hyperbolic Tangent, Sigmoid, Step, ReLU (Mengi & Metlek, 2020)	Hyperbolic Tangent
	2nd Hidden Layer	1-250	10
	2nd Hidden Layer Activation Functions	Hyperbolic Tangent, Sigmoid, Step, ReLU	Sigmoid
Output Layer	Output	1	1
	Number of Iteration	100-10,000	1,000
	Number of error rate	0.0001 – 0.01	0.01

When the data were tested for the number of layers in the range of 1-10, it was found that the training time was extended, despite that, the system performance decreased. Therefore, in the study, a two-layer structure with optimum values was preferred.

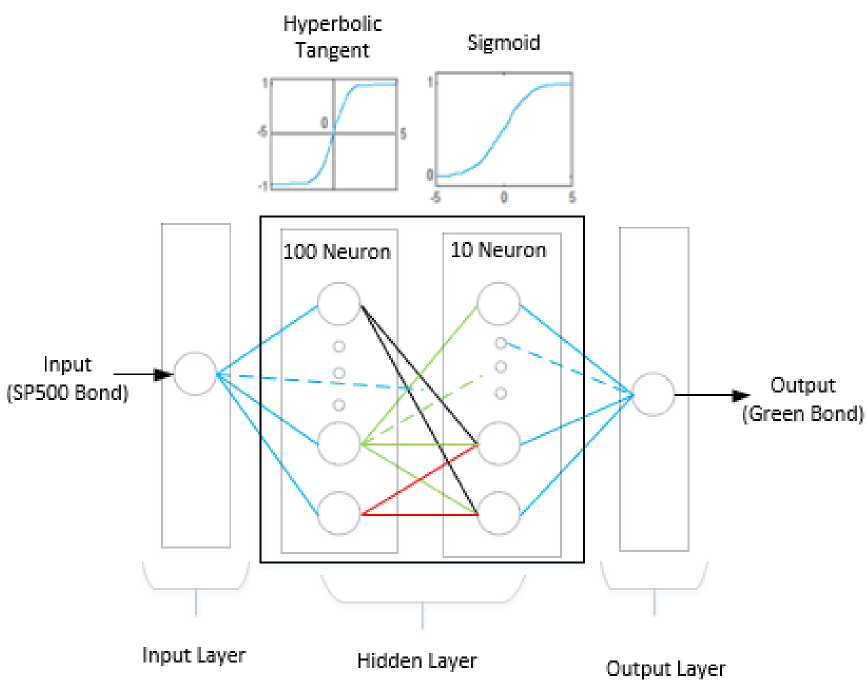

Figure 4: Designed MLF-ANN Model

The mathematical expression of the designed two-layer MLF-ANN model is shown in Equation 12 with the notation used in Section 3.2.

$$Y_{ik} = sigmoid_{k=1}^{10}\left(\sum_{k=1}^{k=10} X_k tanh_{ik=1}^{100}\left(\sum_{ik=1}^{i=100} X_{ik}W_{ik} + \beta w_{ik}\right) + \beta w_k\right) \tag{12}$$

Equation 12 formulates the forward computing of the multilayer feedback artificial neural network model used in the study in general terms. Of the data used in our study, 80% were split as training data and 20% as test data. The sub-indices *ik* and *k* in equation 12 represent the values of the training and test data given to the network at that moment. Y_{ik} represents the output of the system that forecasts S&P Green Bond index value 1 day later with X_{ik} S&P 500 Bond index input data. Y_{ik} represents the output of the system that forecasts the S&P Green Bond index value with the input data (X_{ik}) of the last 5 days (*t-1* to *t-5*) average value of the S&P 500 Bond index. The *w* in this equation represents the weight coefficients. At the beginning of the computing, these weight coefficients are randomly assigned by the system. Once the network is run in the forward direction, the values that the network should find are compared with the actual values. The difference is considered an error. The main factor causing this error is the randomly determined weight coefficients. The obtained error value affects these weight coefficients by using the backpropagation algorithm and new weight coefficients are calculated. Then the network is restarted. Optimum weight coefficients obtained at the end of 1000 iterations are used in Equation 12. After the training of the network is completed, this time the data that it has not seen before, namely the test data (20% of the data) is given as input, and the system is run again in the forward direction and the overall success of the system is measured. Here, the error functions presented in Equations 7-11 are used to measure the system's success.

4. Findings

The MLF-ANN model was designed to forecast the S&P Green Bond Index. The predictive success of the model was measured by Equation 6-10 and the performance results are presented in Table 6.

Table 6: Performance Results

Error Function	Error Value / Rate
Mean Absolute Error (MAE)	1.2552
Mean Squared Error (MSE)	3.0700
Root Mean Square Error (RMSE)	1.7522
Mean Absolute Percentage Error (MAPE)	0.0113
Regression Determination Coefficient (R^2)	0.9893

In Table 6, the results of the regression determination coefficient (R^2) reveal a strong regression relationship of 98.79% between the forecasted and actual green index values. In addition, the error function results show that the error margin of the designed model is quite low. In the literature, the prediction performance of models with a MAPE below 10% is defined as "very good"(Yakut et al., 2014). Since the MAPE value of the designed model is 1.13%, well below 10%, it can be said that the prediction performance of the model is quite good.

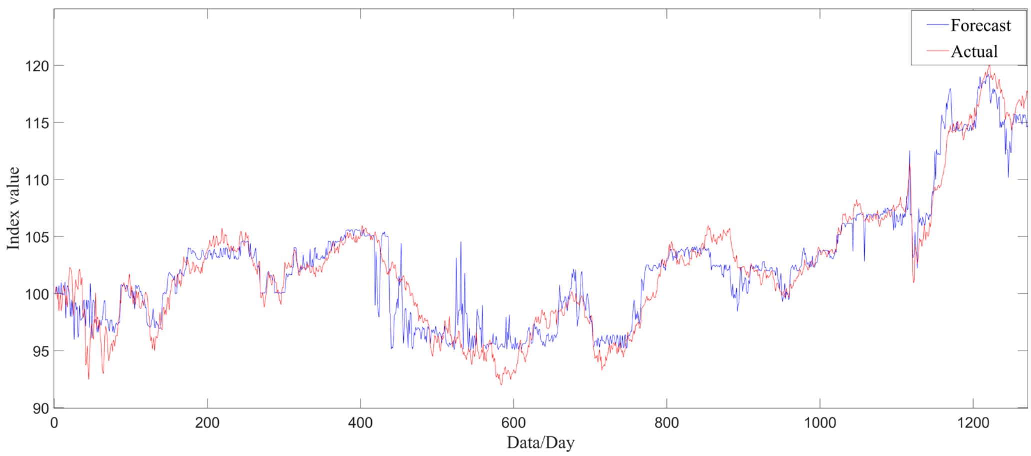

Figure 5: Forecasted and Actual S&P Green Bond Index Chart

In Figure 5, the red lines are representing the actual values of the S&P Green Bond index and the blue lines representing the forecasted values calculated by the designed MLF-ANN model overlap to a large extent.

5. Conclusion and Discussion

Increasing environmental awareness despite the threat of climate change has led to an increased demand for climate projects in the last decade. The unique characteristics of climate projects necessitated the development of special capital market instruments for their financing. The most widely used of these instruments are green bonds. Green bonds integrate the trust factor of fixed-income instruments with environmental awareness in the long-term financing of climate projects (Çetin, 2021).

There are some studies showing a strong price connectedness between green bond and conventional bond markets (Broadstock & Cheng, 2019; Reboredo, 2018). Based on these studies this paper is designed to use the conventional bond index as a predictor to forecast the green bond index with artificial neural networks. In the study, the S&P green bond index is used as an indicator of the international green bond market, and the S&P 500 bond index is used to represent the conventional bond market. Due to the multivariate non-linear nature of financial time series, it is very difficult to predict the asset price with a single input with high accuracy. However, in this study, a single input variable (S&P 500 Bond Index) was used and the S&P green bond index was forecasted with a 1.13% MAPE and 98.93% R^2. Similarly, Ngwakwe (2021) forecasted the S&P green bond index with 1.31% MAPE and 0.771395 R^2 findings using the Linear Regression model. Comparatively, the forecasting performance achieved with the designed ANN model in this study is more accurate than the values obtained by Ngwakwe's study as a lower error rate and a higher regression determination coefficient.

The high forecasting performance in ANN models requires evaluating the possibility that the network may have memorized it. In the designed model, cross-validation was applied by splitting the data according to the k-fold 5 value and thus the possibility of memorization of the network was prevented. In this case, the high forecasting performance of the network should be related to the success in the selection of the input variable as the S&P 500 bond index and the suitability of the designed MLF-ANN network architecture to the data. In the high accuracy forecasting of the green bond index value, the selection of the input parameter has a significant role in addition to the success in selecting and designing the model. As stated earlier, there is a strong connection between the price movements of the green bond market and the conventional bond market (Broadstock & Cheng, 2019; Reboredo et al., 2020; Reboredo & Ugolini, 2020). The existence of this bond may be primarily due to the fact that the fundamental characteristics of green bonds are largely the same as conventional bonds. Because, both bond markets have similar features such as coupon payment period and method, presence of a secondary market, high liquidity as well as offering fixed income investment instruments. The most distinctive feature of green bonds is the obligation to use the fund provided to the issuer in an environmentally friendly project financing to mitigate emissions.

Second, both bond markets are largely influenced by the same macroeconomic factors, although there are differences. As a matter of fact, Broadstock & Cheng, (2019) also revealed in their study that the determinants of the bond between the green and black bond market are macroeconomic factors such as VIX, EPU, ADS, oil prices.

Finally, the dataset used in the research consists of S&P green bond and S&P 500 Bond index values published by S&P. The methodology used by S&P in pricing these indices is also similar (Standard and Poors', 2021b, 2021a).

Generally, these findings lead us to two significant conclusions. First, the ANN model is an effective model for forecasting green bond index value. Second, the conventional bond is the predictor of the corporate green bond index values. Specifically, the S&P 500 bond index is the determinant of the S&P green bond index values, which consists of 9,953 corporate green bonds. Forecasting such a large-scale index will reduce uncertainty for green bond markets and provide benchmarking for investors and market makers. Moreover, it offers investors significant advantages such as maximizing profits or minimizing losses.

In future works, green bond index values can be forecasted with other artificial intelligence and deep learning models. In order to improve the forecasting accuracy, different input variables can be added to the model.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and article preparation.

Conflict of Interest

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Resume

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