European Journal of Technique

journal homepage: https://dergipark.org.tr/en/pub/ejt

Vol.14, No.2, 2024

Research Article

Greenhouse Gas Emission Estimation by Artificial Intelligence

Serkan Ertugrul[1*] and Prof. Dr. Necmettin Sezgin[2]

[1*]Batman University, Electrical and Electronics Engineering Department, Batman, Turkey. (e-mail: serkanertugrul@gmail.com).

[2] Batman University, Electrical and Electronics Engineering Department, Batman, Turkey. (e-mail: necmettin.sezgin@batman.edu.tr).

ARTICLE INFO

Received: Jul., 44. 2023
Revised: Sep., 21. 2023
Accepted: Aug, 28. 2024

Keywords:
Deep Learning
Climate Change
Global Warming
Greenhouse Gas
Artificial Neural Networks

Corresponding author: *Serkan Ertuğrul*

ISSN: *2536-5010* | e-ISSN: *2536-5134*

DOI: https://doi.org/10.36222/ejt.1327275

ABSTRACT

Human activities, particularly the burning of fossil fuels for energy production, industrial processes, and transportation, release significant amounts of greenhouse gases into the atmosphere. Global agreements such as the Paris Agreement have started expressing the goal of reducing human activities and achieving net zero emissions. It is expected that all countries will set targets and work towards reducing greenhouse gas emissions by implementing sustainable and realistic programs. By utilizing data such as financial indicators, population, afforestation, Human Development Index (HDI), and energy consumption, machine learning methods were employed to calculate future greenhouse gas emission levels in some countries. For this purpose, a comparison was made by using deep learning methods, such as Long Short-Term Memory (LSTM) and a hybrid CNN-RNN model, separately with the help of the MATLAB program. Additionally, future greenhouse gas emission predictions were made by comparing the results of the study using LSTM modeling with the predictions obtained through NARX modeling for time-series data. The aim was to emphasize the need for countries to develop sustainable programs by considering various data in order to achieve their greenhouse gas emission reduction targets.

1. INTRODUCTION

This study aims to calculate future greenhouse gas emission levels in Turkey and the United States using financial, economic, and human development indicators, population data, afforestation rates, and energy consumption data. Through a comprehensive analysis of countries' activities contributing to global warming and by bringing together different data sources and utilizing machine learning methods, the study seeks to determine the potential greenhouse gas emissions of countries and provide possible forecasts for actions to prevent these emissions. Turkey and the United States, with their diverse geographical, economic, and social characteristics, provide an important comparison for the development of strategies to combat climate change. Similarly, by selecting examples from different locations, both developed and developing countries can serve as references for designing and implementing effective policies to reduce greenhouse gas emissions. The study aims to contribute to establishing a sound methodology for planning and implementing measures in industries, agriculture, energy, and other facilities without hindering countries' sustainable development, in order to make the most appropriate plans.

It also conducts comparisons using deep learning methods such as Long Short-Term Memory (LSTM) and hybrid CNN-RNN models to achieve emission reduction goals. Additionally, future greenhouse gas emission predictions are made by comparing LSTM modeling results with those obtained through NARX modeling for time-series data. This study, by emphasizing the importance of data-driven strategies in combating greenhouse gas emissions, has the potential to contribute to the development of sustainable programs that help countries reach their emission reduction targets.

The increasing population, industrialization, and urbanization have greatly polluted the environment, and the continued use of fossil fuels has resulted in increasing environmental damage [1].

The Keeling Curve is a curve used to describe the increase in carbon dioxide levels in the atmosphere [2]. It was established by Charles David Keeling, who collected samples from the Mauna Loa Observatory (MLO) located 3 km above sea level. The measurements taken between 1958 and 2005 demonstrated a rising curve (the Keeling Curve), providing the first evidence of the warming occurring in the atmosphere [3]. The Record of Atmospheric CO2 Concentration Measured at the Mauna Loa Observatory from 1958 to 2022 can be seen in Figure 1.

In Article 4 of the Paris Agreement, it is stipulated that greenhouse gas emissions in the atmosphere should reach their peak as soon as possible and then be reduced, with the aim of achieving a balance between emissions and sinks by 2050. The IPCC (The Intergovernmental Panel on Climate Change)'s Special Report on 1.5 Degrees has highlighted the importance of limiting global temperature rise to 1.5 degrees by 2030 and striving to achieve zero degrees by 2050 for the continuity of natural life. The "Glasgow Climate Pact," previously agreed upon at the 26th Conference of the Parties (COP 26) of the United Nations Framework Convention on Climate Change (UNFCCC), was reiterated as a target during the conference [4].

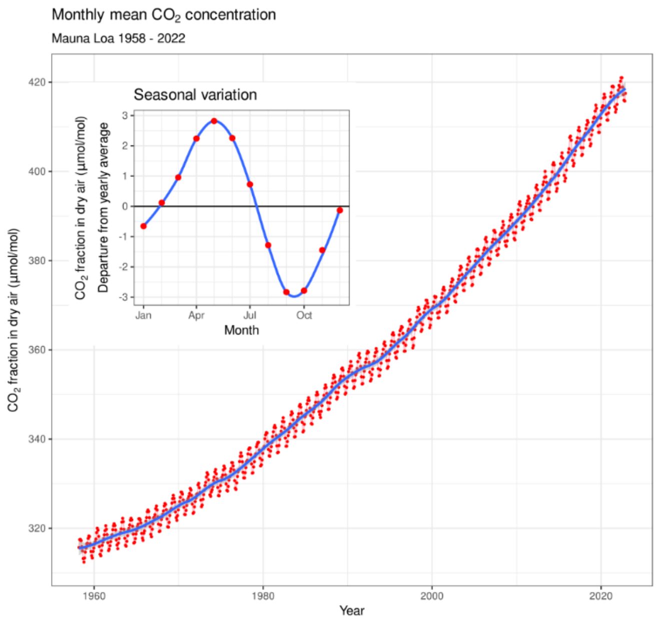

Figure 1. Atmospheric CO_2 concentration measured at the Mauna Loa Observatory (1958-2022) [5]

The increasing population and advancing technology, along with anthropogenic influences, are causing changes in the global climate, which in turn have negative impacts on biodiversity and biological life on Earth [6].

According to the information available on the website of the Ministry of Environment, Urbanization, and Climate Change (2022), the Paris Agreement, which was achieved during COP 21 in 2015, aimed to come into effect after countries responsible for 55% of greenhouse gas emissions committed to fulfilling the conditions outlined in the agreement. This target was achieved on November 4, 2016. The agreement also includes provisions for developed countries to plan the flow of finances in order to ensure low greenhouse gas emissions without compromising food production. Countries that are party to the agreement are required to submit their "National Determined Contributions" that include activities carried out every five years.

According to information published on the United Nations official website in 2022, the Sustainable Development Goals (SDGs) aim to tackle climate change by considering education, health, social protection, and employment opportunities, along with an economic growth strategy. The SDGs emphasize the need to integrate these aspects in the fight against climate change [7].

2. RELATED WORKS

Machine learning methods, specifically "Decision Tree Modeling", "Artificial Neural Networks" and "Support Vector Machines" were employed to predict the trends in carbon dioxide (CO_2) emissions resulting from human activities for European Union countries and Turkey. The results indicated a decreasing trend in CO_2 emissions in advanced European countries while an increasing trend was observed in Turkey [8].

The Grey Wolf Optimization (GWO) method was applied using data related to Gross Domestic Product (GDP), energy consumption, renewable energy production, population, and urbanization rates. Among various artificial neural network models, the GWO optimization method outperformed others, including Backpropagation Algorithm, Artificial Bee Colony (ABC), and Teaching-Learning Based Optimization (TLBO). The study projected that there would be a reduction in greenhouse gas emissions in Turkey until 2030 [9].

Another study used an artificial neural network model to investigate the intensity of greenhouse gas emissions in Australia, Brazil, China, India, and the United States. The model considered nine different parameters, including economic growth, energy consumption, financial development, research and development (R&D), foreign direct investment, trade openness, industrialization, and urbanization. Different models were applied to various countries using quarterly data from 1980 to the end of 2015. The Backpropagation Algorithm with a Multi-Layer Perceptron achieved nearly zero error in prediction [10].

To model CO2 emissions using energy consumption data for various energy sources and Gross National Product (GNP) between 2000 and 2009, the Group Method of Data Handling (GMDH) among artificial neural network models was employed. The study observed that the model, despite providing R2 (R-squared) values close to zero for training, testing, and overall data, achieved successful predictions with values close to zero for the Absolute Average Relative Deviation (AARD) [11].

In a study encompassing countries in Southeast Asia, such as Malaysia, Indonesia, Singapore, and Vietnam, the modeling of carbon dioxide (CO_2) emissions resulting from various energy sources was conducted. Given the significance of energy consumption in the economy, Gross Domestic Product (GDP) data, an economic indicator, was considered. Two artificial neural network (ANN) models with normalized radial basis and tansig transfer functions were employed for modeling CO_2 emissions successfully [12].

In this study, particular emphasis is placed on the utilization of a broader range of data, including economic indicators, population, and afforestation rates, alongside energy-related information. Additionally, the study highlights the wider time span covered in the dataset compared to previous studies.

3. MATERIAL and METHODOLOGY

3.1. Data Collection

Since 1990, many countries have initiated efforts to combat greenhouse gas emissions by establishing greenhouse gas inventories through the Vienna Convention. However, with the Paris Agreement in 2015, countries started to place more importance on greenhouse gas inventories and improve their record-keeping based on their commitments. In this study, monthly data was obtained, but if such data was unavailable, annual data was used instead. The annual data was then converted into monthly distributions by considering the "Keeling Curve," which predicts monthly variations in a sinusoidal pattern that increases each year.

For each country, the data used in this study was obtained within specific time intervals. The study begins with data from January 1970 and ends with data from December 2022.

Between these dates, any missing data is generally filled using the earliest recorded data from January 1970 up to the first available data point. If the last recorded data is from a date prior to December 2022, it is used to fill in the missing data until December 2022. If sufficient data is not available, it means that particular data is not used for that country. In the context of this study, the Table 1 indicates which dataset was used for the United States and Turkey, denoted by a "+" sign.

TABLE I
THE DATA MARKED WITH "+" WAS USED FOR GREENHOUSE GAS EMISSION ESTIMATION FOR THE UNITED STATES (USA) AND TURKEY (TUR)

Definition	Unit	USA	TUR
Total CO2 Emissions from Energy	Metric Tons of Carbon Dioxide	+	-
Greenhouse Gas Emissions	Mton CO2e	-	+
Human Development Index	Index	+	+
Forest Area	Forest Land Area in km2	+	+
Population	People	+	+
Gross Domestic Product - GDP	Base Year 2010=100 (USD per capita)	+	+
Net National Income	Base Year 2010=100 (USD per capita)	+	-
Gross National Income - GNI	Base Year 2010=100 (USD per capita	+	+
Producer Price Index for All Commodities	Base Year 2010=100	+	+
Consumer Price Index	Base Year 2010=100	-	+
Financial Market Prices End-of-Period	Base Year 2010=100	+	-
Industrial Production Economic Activity Index	Base Year 2010=100	+	+
Long-term Investment Rates, Annual Percentage	Base Year 2010=100	+	-
Primary Energy	MLN_TOE	-	+
Renewable Energy	KTOE	-	+
Total Primary Energy Consumption	(Trillion Btu)	+	-
Total Renewable Energy Consumption	(Trillion Btu)	+	-

Greenhouse Gas Data: Greenhouse gas data includes all fossil CO2 sources related to the combustion of fossil fuels, metal production processes, urea production, or agricultural solvent use. However, these data do not include emissions from savannah burning, forest fires, land use changes, forestry, and biomass burning. Emissions from fluorinated gases are based on country reports whenever possible, and if not available, they are included in the reports using data from the United Nations Environment Programme (UNEP), scientific literature, and expert opinions. For countries other than the United States, the studies were conducted based on greenhouse gas emission data available in the Emissions Database for Global Atmospheric Research (EDGAR) system. Table 2 presents the greenhouse gas emission values in Mton CO_2e for selected countries and sectors during the years 1970 and 1974.

TABLE II
GREENHOUSE GAS EMISSION VALUES IN MTONCO_2E FOR SOME COUNTRIES AND SECTORS FOR 1970 AND 1974 [13]

EDGAR Country Code	Country	1970	1971	1972	1973	1974
TUR	Turkey	103	108	116	122	126
GBR	United Kingdom	886	877	846	886	841
USA	United States	5791	5667	5934	6136	5966

Population Data: The work of the United Nations Statistics Division utilized data from country population records to compile the available information.

Human Development Index (HDI) data is obtained from the official website of the United Nations Development Programme (UNDP), which has been maintaining records on an annual basis since 1990 [14].

Gross National Income (GNI) data, which represents gross domestic product excluding production subsidies, net income from abroad, and net taxes, can be found in the inventory of economic data maintained by the Organisation for Economic Co-operation and Development (OECD). However, these values do not include income sent by foreigners in the country back to their own countries. Total annual Gross National Income values in terms of per capita dollars were used in this study [15].

Net National Income (NNI) is derived by subtracting the depreciation of fixed capital assets from gross national income and is included in the inventory of economic data for member countries maintained by the Organisation for Economic Co-operation and Development (OECD). In this study, the total annual Net National Income value in terms of per capita dollars was used [16].

Gross Domestic Product (GDP): The United Nations Statistics Division (United Nations, 2023) provides access to Gross Domestic Product (GDP) data, which represents the annual final goods and services for member states based on their statistical data. Per capita GDP data in terms of dollars for the respective countries in the year 2021 were used [17].

Financial Indicators: The International Monetary Fund (IMF) was established to meet the payment balance needs of its member countries [18]. The IMF utilizes various indicators, such as the consumer price index, producer price index, seasonally adjusted industrial production, industrial production economic activity index, and end-of-period financial market prices, to maintain inventories related to the financial conditions in countries. These indicators are evaluated in percentage units, with the data based on the 2010 figures as the baseline. The data utilized for these indicators are stored in the International Financial Statistics database.

The Organization for Economic Cooperation and Development (OECD) or the Organisation for Economic Co-operation and Development provides a wealth of data in the "Main Economic Indicators" (MEI) section on their website. These data cover various areas such as transportation, economic projections, finance, production, education, agriculture, and fisheries. Among these data, there is the indicator of "Long-term Investment Rates." With globalization, maturing markets, complex actors, advancing technologies, and evolving regulatory frameworks, financial indicators have gained importance. Data such as "Long-term Investment Rates" are used because they indicate the financial conditions of countries, which are crucial for achieving net-zero emission targets in greenhouse gas emissions through strong and evolving financial circumstances [19].

Primary energy sources are the natural forms of energy that are used directly. These sources include coal, oil, natural gas, nuclear energy, biomass, hydro power, solar energy, wind energy, wave energy, and tidal energy. These primary energy sources can be further processed or transformed into secondary energy sources. Secondary energy sources include electricity, gasoline, diesel, kerosene, secondary coal, coke, petroleum coke, air gas, and liquefied petroleum gas (LPG). Among renewable energy sources, there are hydro power, solar energy, biomass, wind energy, geothermal energy, wave energy, tidal energy, and hydrogen. The increase in population, rise in living standards, and technological advancements lead to an increased energy demand. This growing energy demand can be met through planned use of non-renewable energy sources and greater utilization of renewable energy sources [20].

According to the Organisation for Economic Co-operation and Development (OECD) website, primary energy supply refers to the energy production needed, and in the data used, it is calculated based on the calorie content of energy products, expressed in metric tons of oil equivalent (toe). One metric ton of oil equivalent is equal to 107 kilocalories or 41.868 gigajoules [21].

According to the Organisation for Economic Co-operation and Development (OECD) website, renewable energy sources contribute to primary energy supply. Renewable sources include hydro power, geothermal energy, solar energy, wind energy, tidal energy, wave energy, hydrogen, and biofuels. These contribute to primary energy supply in terms of primary energy equivalents, except for pumped hydro storage method. Additionally, renewable energy includes bio-gasoline, biodiesel, biogas, renewable energy derived from urban waste, biomass (material obtained from living or recently living organisms) directly or indirectly produced fuels, wood, plant residues used for energy production, ethanol, animal materials or waste, sulfite liquor, and waste disposed of in a centralized location for heat and/or electricity production [22].

U.S. Primary and Renewable Energy Consumption with CO2 Emission Data: The U.S. Energy Information Administration (EIA) provides access to monthly CO2 emission data for total energy in the United States starting from January 1973 on their official website. Additionally, both Primary Energy Consumption and Renewable Energy Consumption data can be accessed in British Thermal Units (BTU) on an annual basis starting from January 1973 [23].

Afforestation: According to the official website of the World Bank, the organization collaborates with various countries and partners to promote sustainable forest management through informative programs related to the forest sector, strengthening countries' political commitments through long-term programs aimed at sustainable forest management. Forests contribute to national economies in areas such as employment, food, and energy, and play a significant role in addressing climate change. Particularly, wood-based fuels serve as an important energy source for Africa and offer an alternative to fossil fuels. Therefore, sustainable forest management is of great importance. Forests are also crucial ecosystems for soil fertility, water basins, and habitats for living beings. One of their most important features is their ability to absorb CO2 from the atmosphere, thus helping to mitigate climate change [24].

3.2. Data Organisation

For this study, January 1970 was established as the starting point, and December 2022 was used as the endpoint for data collection. During this timeframe, some data gaps were identified. These missing data points either pertained to periods before the initial recorded data or could be from periods preceding December 2022, which was the final data point. In such cases, missing data points were filled by extending the data from the initial recorded date in January 1970 up to the respective starting date of the missing data. Similarly, if the final recorded data date was earlier than December 2022, any missing data within that period was completed using the final recorded data. Input data sets with extensive missing data were excluded from the study. This approach ensured that gaps resulting from missing data were addressed, rendering the data suitable for analysis.

For the United States, greenhouse gas emissions and primary and renewable energy source data were collected on a monthly basis. For Turkey, greenhouse gas emission data was obtained annually. These yearly data sets were transformed into monthly data points following a sinusoidal pattern for each year, considering the "Keeling Curve." Other data sources were retrieved from databases available on the official websites of the United Nations, IMF, OECD, and the European Union. Some economic or financial data were converted into percentage values based on the 2010 data, or they were used in their converted forms as provided by the data source organization. Yearly data for population and forest areas were maintained at constant values for each month within the respective year. In addition, for other input data, if yearly data were available, they were evenly distributed across each month.

3.3. Deep Learning (LSTM and CNN-RNN) and ANN

In the study that combines data such as greenhouse gas emissions, economic indicators, population, and afforestation for the purpose of deep learning, each data was individually evaluated and a single output was obtained by predicting future data that would encompass all the information in a single time series.

To achieve good performance in deep learning, it is essential to ensure an adequate amount of data. Additionally, in deep learning, networks can be observed during training to see how they adapt to the curve. The network continues training with iterations. Throughout the training process, corrected training accuracy curve, uncorrected training curve, and validation curve can be observed. Additionally, the loss training accuracy curve, uncorrected training curve, and validation curve can also be observed.

Initially, the LSTM Regression algorithm, which is one of the deep learning methods, was used. Then, a CNN-RNN hybrid method, another deep learning approach, was applied specifically to greenhouse gas emissions data of the relevant countries, and the results obtained from the LSTM Regression algorithm were compared for validation.

Each data was analyzed separately using the Deep Network Designer. The dataset used for analysis included known data from January 1970 to December 2022. Based on this study, predictions were made for the period from January 2023 to March 2028. The predicted data covered approximately 10% of the available information. Thus, predictions were made using 636 monthly data points for each data and 63 months of future predicted data were obtained. In total, a dataset of 699 monthly data points was generated.

Artificial Neural Network (ANN) with NARX modeling can be used for time series forecasting. With its feedback structure, it is a dynamic ANN model commonly used for nonlinear data inputs. In the predictions made using artificial neural networks, greenhouse gas emissions were selected as the target variable, and other data were used as input variables. The accuracy of the predictions was tested using a randomly selected 15% of the data with the Regression R-value. The NARX model based on the artificial neural network demonstrated successful prediction of greenhouse gas emissions at the country level with different input variables, confirming the relationships between the data [25].

3.3.1. Deep Learning with LSTM

Long Short-Term Memory (LSTM) is different from feedforward artificial neural networks; it has a recurrent structure. After the preliminary data preparation, the Deep Network Designer tool in Matlab was used for each data input. In the design of deep learning, a sequence was created using layers from the library. A Sequence-to-Sequence LSTM regression model with 5 different layers was chosen for prediction.

The first layer used a time series data sequence as input. In the second layer, "Long Short-Term Memory (LSTM)" was employed for predicting from time series or sequential data. The LSTM layer was trained, and the output data was obtained with only a single time series data input. 128 hidden units were chosen for the LSTM layer. The LSTM layer is a recurrent neural network (RNN) layer that learns long-term dependencies between data points based on the time series.

In the third layer, a "Dropout Layer" was used with a probability value of 0.5 to prevent overfitting and underfitting, aiming to improve the model's performance in deep learning tasks. In the fourth layer, a "Fully Connected Layer (FC Layer)" was used to connect to the neuron layer from the previous layer. Weight matrices and bias were included in the computations to enhance the outputs, and a single output was selected.

The final layer used a "Regression Layer" to calculate Mean Squared Error (MSE) for regression tasks. It provides an absolute value by calculating the average of the squared differences between the actual value from the model outcome and the target value, thus measuring the distance.

In the "Deep Network Designer," a network was created sequentially using single-row data input, consisting of an input layer, LSTM layer, a "drop" layer, a fully connected layer (FC) with a single output, and a regression layer. The analysis was performed using a 5-layered "Sequence-to-Sequence LSTM Regression model" without encountering any errors or warnings. The design and suitability of the model were verified after configuring the layers and settings in the "Deep Network Designer" in Matlab, as shown in Figure 2 in the research.

ANALYSIS RESULT

	Name	Type	Activations	Learnables
1	input Sequence input with 1 dimensions	Sequence Input	1	-
2	lstm LSTM with 128 hidden units	LSTM	128	InputWeights 512×1 RecurrentWe… 512×… Bias 512×1
3	drop 50% dropout	Dropout	128	-
4	fc 1 fully connected layer	Fully Connected	1	Weights 1×128 Bias 1×1
5	regressionoutput mean-squared-error	Regression Output	1	-

Figure 2. Stages of Deep Learning with LSTM

In deep learning, achieving good performance requires ensuring sufficient data size. Additionally, in the "Training Options" section of deep learning, options for training the network are observed. In the "Solver" section, options for optimizers such as Stochastic Gradient Descent with Momentum (SGDM), Root-mean-square Propagation (RMSProp), and Adaptive Moment Estimation (Adam) can be selected for training. With "Adam," different learning rates can be specified for different layers, and it performs well in terms of training speed. In this study, Adam was employed, enabling the setting of distinct learning rates for individual layers, resulting in enhanced training speed. A learning rate of 0.005 was chosen for this study. Additionally, "MaxEpochs" was set to 500, "Batch Size" to 128, "Gradient Threshold" to 1, and for weight decay, the "Gradient Threshold Method" was selected as "L2 norm."

3.3.2. Deep Learning with CNN-RNN

In this study, a hybrid approach combining CNN and RNN was employed to make predictions for future. CNN was used to extract features related to the given sequence in the time steps, while RNN was utilized to predict the values in the subsequent sequences over time.

Pre-trained CNN models have been found to expedite learning and enhance accuracy by leveraging weights from similar existing problems. In Inception pre-trained networks, operations are modularly processed in self-filtering and pooling layers simultaneously. Meanwhile, Xception networks, an extension of Inception, utilize smart depthwise and pointwise convolutions [26]. Recurrent Neural Networks (RNNs) are adept at handling time-series data like speech recognition, thanks to their ability to exhibit temporal dynamics by forming loops between nodes. Derived from feedforward neural networks, RNNs effectively process variable-length input sequences for tasks such as handwriting or speech recognition.

The study was conducted using the "Deep Learning Toolbox," one of the Matlab tools. In addition, in the example, the Xception network architecture was chosen, with 600 "MaxEpochs," a learning rate of 0.00611, feedforward learning, and the "adam" solver. Approximately 90% of the data was used for training purposes, and the remaining 10% was used for testing. Training was conducted using the "Deep Learning Toolbox" with Bayesian Optimization. After a correlation method based on sMAPE (Symmetric Mean Absolute Percentage Error) was used to verify the percentage error between the tested and predicted values, R-values were examined. Following these stages, predictions were made for future data, i.e., the steps after the last sequence, using the trained network [27].

In this study, which utilized a hybrid approach combining CNN-RNN algorithms, the results obtained with the LSTM algorithm, previously used for predicting the greenhouse gas emission levels of the United States and Turkey, for the next 63 months were compared. This comparison allowed for assessing the accuracy solely for the target data, thus providing a preliminary comparison for the next artificial neural network study.

3.3.3. Artificial Neural Networks (ANNs)

In this study, deep learning models were employed to make predictions about the future using data from the United States and Turkey. After this stage, predictions were made using a time-series neural network tool in an artificial neural network, and the accuracy of these predictions was evaluated.

Predictions regarding the future were made using deep learning, employing different data for the United States and Turkey. Subsequently, greenhouse gas emission predictions were conducted using the artificial neural network time series tool, utilizing relevant data for different countries. The greenhouse gas emission predictions obtained with ANN, considering data on energy, economic, developmental, population, and deforestation for each country, were compared and evaluated against the results obtained from LSTM and CNN-RNN studies.

For each dataset, Deep Network Designer was used separately to obtain data up to December 2022, which accounted for 10%

of the available data. In other words, predictions were made for the future from January 2023 to March 2028. Thus, for each dataset, predictions were made for the next 63 months using a total of 636 months of data, resulting in 699 months of data in total.
NARX modeling can be used for predictive purposes in time series data. It is a dynamic artificial neural network model typically employed for non-linear data inputs in feedback-used networks [28]. A network structure was created using the 'NARX Neural Network' in Matlab with the 'ntstool', as seen in Figure 3.

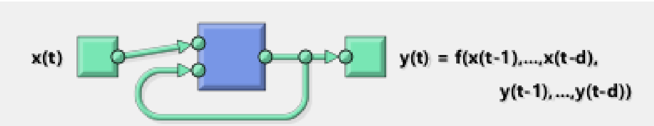

Figure 3. Illustrates the structure of the NARX (Nonlinear AutoRegressive with eXternal (eXogenous) Input) model (x(t) input sequences, past values of d y(t), y(t) prediction sequences)

Nonlinear AutoRegressive with eXternal (eXogenous) Input (NARX) modeling was used with random selections and Bayesian Regulation after data preprocessing. Performance measurement was done using Mean Squared Error (MSE) and the correlation coefficient (R). In Matlab's "ntstool," the NARX model was selected, and for the United States, "Total Energy CO_2 Emission" data was chosen as the output data, while the others were selected as input data. For the other countries, "Greenhouse Gas Emission" data was selected as the target data, and the other data were used as input.
In the random selections, 70% of the data was used for training purposes, 15% was used for validation, and the model was trained based on validation data. Once validation values were reached, the training was completed. The remaining 15% was used for testing.
The number of hidden layers to be used in the NARX neural network model and the "number of delays (d)" were selected. The network was set to "open loop."
In Figure 4, following the selection of the 'NARX Neural Network' application using Matlab's 'ntstool', details such as the number of input data, output data, hidden and output layer information, as well as output data counts, can be observed. Additionally, within the hidden layer, the circular shape indicates the time interval between input and output data. In the 'ntstool', the term 'number of delays (d)' represents the time interval between input and output data. This parameter determines the time interval over which past data will be used in predicting future values. A higher value of 'd' allows for predictions considering a longer time interval, while a lower value of 'd' results in predictions based on a shorter time interval. This parameter is crucial for making accurate predictions.

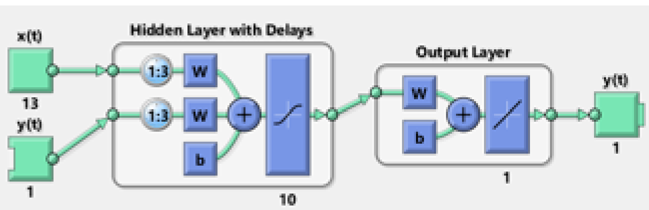

Figure 4. An example neural network model obtained from the Matlab application

Three training algorithms were available: "Levenberg-Marquardt," "Bayesian Regularization," and "Scaled Conjugate Gradient." Bayesian algorithm, although it may take some time for datasets with noise and limited data, tends to provide good results as the R-value approaches 1. The goal of the training was to achieve results as close as possible to this outcome.

4. RESEARCH RESULTS AND DISCUSSIONS

4.1. Future Predictions with LSTM

In the prediction made for the United States, 14 features were used, and greenhouse gas emissions were selected as the target variable and others were used as input. For each feature, the "Deep Learning" LSTM algorithm was applied, resulting in RMSE values ranging from 0.3 to 0.1 and close-to-zero values for the loss curve. The graph Figure 5 illustrates the prediction data for the United States' "Total Energy CO2 Emissions" after deep learning training, starting from January 2023 and covering a future period of 63 months.

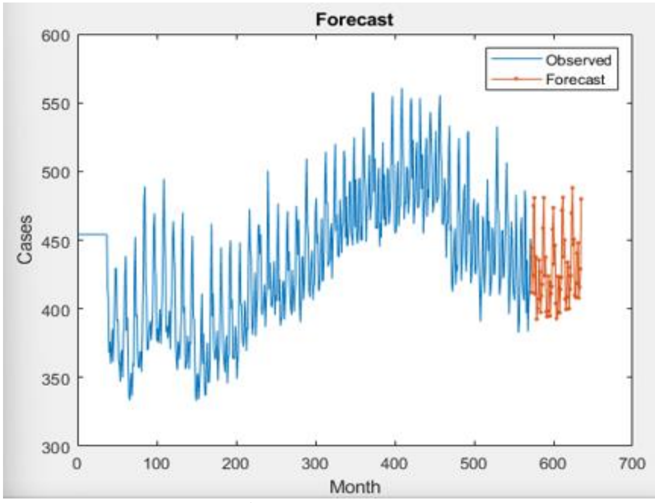

Figure 5. Predicted values for monthly "Total Energy CO2 Emissions" in the United States using "Deep Learning" after training

In the prediction made for Turkey, 10 input variables were used, and one greenhouse gas emissions target was set. For each input variable, LSTM Regression algorithm was used in Deep Learning to perform the training. The RMSE values obtained during the training process range from 0.3 to 0.1, and the values on the "Loss" curve are close to 0. The graph Figure 6, depict the greenhouse gas emissions for Turkey and the corresponding prediction data for the future 63 months obtained through the training using deep learning.

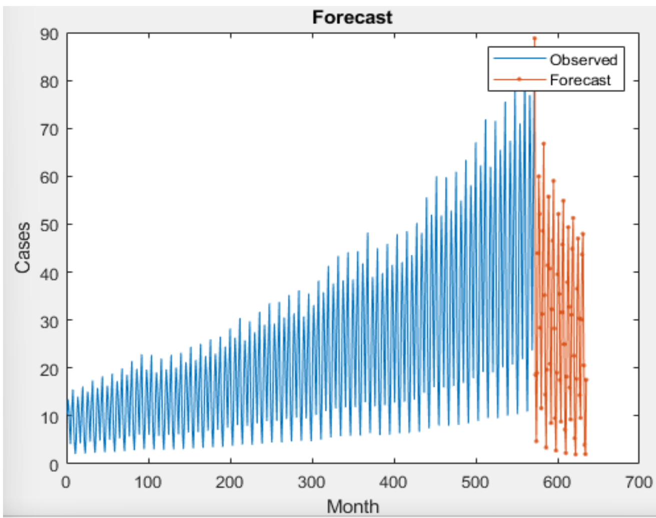

Figure 6. Predicted values for Turkey's annual "Greenhouse Gas Emissions" in the future after training using Deep Learning

The results obtained from the LSTM Deep Learning model for the mentioned data showed significantly low RMSE values compared to the highest values in the dataset. This indicates that the model has learned the data well and achieved low error values. The low RMSE values suggest that the model's predictions are close to the actual values and it performs well overall on the dataset. These results demonstrate that the LSTM Deep Learning model can effectively process the data and make reliable predictions. In the study conducted with Artificial Neural Networks (ANN), greenhouse gas emission values will be used as the target data, while the following data will be used as input data.
For the USA and Turkey, in Table 3 and Table 4, RMSE values and the ratios of RMSE values relative to the maximum value are observed to be below 5% and 8%, respectively.

TABLE III
THE RMSE VALUES FOR THE USA AND THE RATIOS OF RMSE VALUES RELATIVE TO THE MAXIMUM VALUE ARE OBSERVED

Definition	RMSE	The percentage ratios of RMSE relative to the maximum value
Total CO_2 Emissions from Energy	27.56	4.914546071
Human Development Index	0.00	0.280473505
Forest Area	1717.50	0.055386253
Population	3026763.44	0.922620956
Gross Domestic Product - GDP	3.82	2.426800261
Net National Income	4.64	2.995560233
Gross National Income - GNI	2.969	2.226214247
Producer Price Index for All Commodities	1.72	1.255222449
Financial Market Prices End-of-Period	4.17	2.957979744
Industrial Production - Seasonably Adjusted	3.0039	2.629033725
Industrial Production Economic Activity Index	3.35	2.894096362
Long-term Investment Rates, Annual Percentage	0.21	1.338772846
Total Primary Energy Consumption	358.94	3.714064517
Total Renewable Energy Consumption	51.3992	4.282378073

TABLE IV
THE RMSE VALUES FOR TURKEY AND THE RATIOS OF RMSE VALUES RELATIVE TO THE MAXIMUM VALUE ARE OBSERVED

Definition	RMSE	The percentage ratios of RMSE relative to the maximum value
Greenhouse Gas Emissions	7,2559	7,713234463
Human Development Index	0,0044	0,520502626
Forest Area	902,44	0,407869972
Population	578260,00	0,680696704
Gross Domestic Product - GDP	1,4668	1,251027961
Gross National Income - GNI	1,9891	1,693839015
Producer Price Index for All Commodities	17,49	6,453204511
Consumer Price Index	72,15	11,54145272
Industrial Production - Seasonably Adjusted	17,56	8,306708832
Industrial Production Economic Activity Index	24,4698	10,25239306
Primary Energy	355,1154	2,692835215
Renewable Energy	1420200,00	7,288631733

The greenhouse gas values for the years 2020 to 2027 for two countries, as well as the estimated values using the LSTM Deep Learning model for 2023 and subsequent years, are shown in Table 5 in "Mton CO_2e" units.

TABLE V
ACTUAL VALUES FOR "GREENHOUSE GAS EMISSION" BEFORE 2022 IN 'MTONCO_2E' UNITS AND ESTIMATED VALUES FOR 2023 AND BEYOND USING LSTM DEEP LEARNING

	2020	2021	2022	2023	2024	2025	2026	2027
USA	4580	4903	4892	5136	5248	5028	4761	5033
Turkey	586	627	627	523	519	518	542	547

4.2. Greenhouse Gas Emissions - Future Prediction with CNN-RNN and Comparison with LSTM Results

In the context of future prediction using "Deep Learning," the CNN and RNN models were combined and the following regression value was obtained as seen in Figure 7 and 8 for the USA and Turkey, respectively.

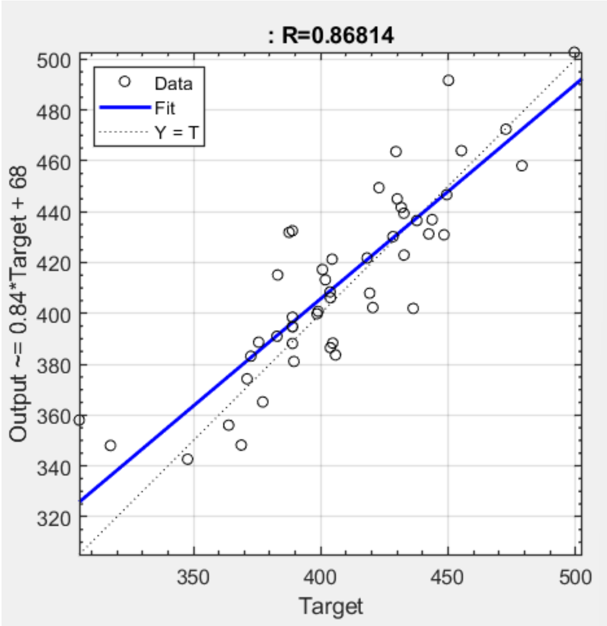

Figure 7. Regression value obtained using CNN and RNN models combined in a hybrid manner for the USA

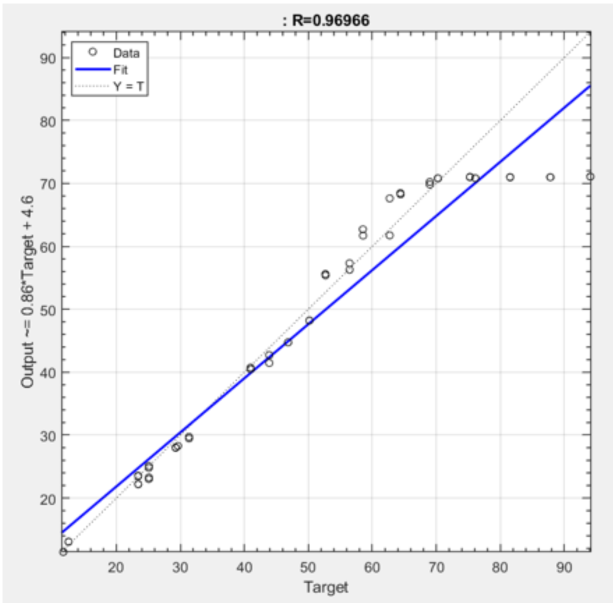

Figure 8. Regression value obtained from the hybrid use of CNN and RNN models for Turkey

The comparison of the R values obtained from the training with the Greenhouse Gas Emission data using the Deep Learning CNN-RNN hybrid model can be seen in Table 6. As observed, the values are close to 1, indicating the success of the training and suitability for prediction studies.

TABLE VI
THE R VALUES OBTAINED THROUGH MODELING WITH THE CNN-RNN HYBRID ALGORITHM IN DEEP LEARNING USING GREENHOUSE GAS EMISSION DATA FOR THE UNITED STATES AND TURKEY

	USA	Turkey
R Value	0,86814	0,96966

Table 7, along with Figures 9 and 10, compare the future greenhouse gas emission predictions obtained through the hybrid application of CNN-RNN using "Deep Learning" with the predictions obtained through LSTM using the Deep Learning method. As seen in the visualization, the results are close to each other.

TABLE VII
MONTHLY GREENHOUSE GAS EMISSION CNN-RNN AND LSTM PREDICTIONS (2025) FOR THE UNITED STATES AND TURKEY IN 'MTON CO_2E' UNITS WITH PERCENTAGE ERRORS

	USA			Turkey		
Month (2025)	CNN-RNN	LSTM	% Error	CNN-RNN	LSTM	% Error
1	422,5	434,2	2,76	17,2	18,299	-6,38
2	443,2	437,2	-1,37	14,44	7,5391	47,81
3	475,8	459,5	-3,42	30,05	26,077	13,23
4	506,8	480,1	-5,26	57,14	51,959	9,07
5	448,7	436,6	-2,69	68,1	75,239	-10,49
6	453,3	437,9	-3,40	55,54	50,567	8,95
7	408,9	407	-0,47	32,21	32,53	-0,99
8	414,2	386,8	-6,61	24,16	19,813	18,01
9	432	378,1	-12,48	52,65	43,071	18,20
10	461,5	390,2	-15,45	69,55	70,684	-1,64
11	454,6	386,3	-15,03	69,65	83,501	-19,89
12	419,2	394,7	-5,86	30,36	38,747	-27,62

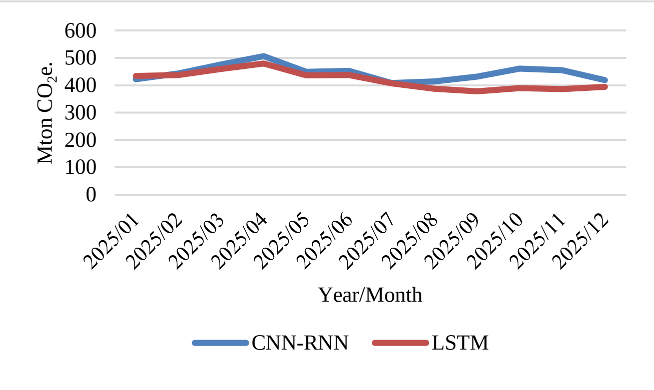

Figure 9. Comparison of Estimated Data for the Months of 2025 for the USA, Obtained with Deep Learning – CNN-RNN Hybrid (Blue Lines) and Obtained with Deep Learning - LSTM Algorithm (Red Line)

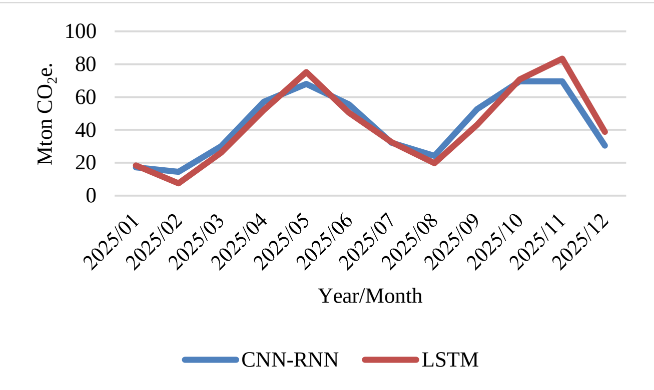

Figure 10. Comparison of Estimated Data for the Months of 2025 for Turkey, Obtained with Deep Learning – CNN-RNN Hybrid (Blue Lines) and Obtained with Deep Learning - LSTM Algorithm (Red Line)

In ANN, greenhouse gas emission values were used as the output data. Therefore, before using the LSTM prediction results for the years 2023 and beyond, the predictions made using the CNN-RNN Hybrid model through Deep Learning were compared with the prediction data obtained using the Deep Learning method. The comparisons yielded similar results, and the reliability of the LSTM Deep Learning method was tested prior to conducting the work with ANN. Table 8 presents the annual estimated greeenhouse gas emission values, along with error values, for both the USA and Turkey. These values closely align with the total values.

TABLE VIII
ANNUAL GREENHOUSE GAS EMISSIONS FOR THE UNITED STATES AND TURKEY FOR THE YEARS 2023 AND BEYOND, CALCULATED USING DEEP LEARNING WITH CNN-RNN HYBRID AND LSTM MODELS (IN MTON CO_2E UNITS)

	USA			Turkey		
Year	LSTM	CNN-RNN	Percentage Difference	LSTM	CNN-RNN	Percentage Difference
2023	5094	5136	0,82	530	523	-1,32
2024	5236	5248	0,23	524	519	-0,95
2025	5341	5028	-5,86	521	518	-0,58
2026	5325	4761	-10,59	519	542	4,43
2027	5285	5033	-4,77	516	547	6,01

4.3. ANN results

The "ntstool" application available in the Matlab program was used to calculate future predictions for the country using the LSTM algorithm and Deep Learning method. These predictions were made using both the entire dataset and the target variable of greenhouse gas emissions. The aim is to effectively establish the relationship between the data variables that influence greenhouse gas emissions for the respective country. The Artificial Neural Network method utilized the Bayesian Regulation training algorithm with a time-series NARX neural network model.

For the USA, after selecting the 'NARX Neural Network' application with Matlab's 'ntstool,' the number of time-series input data used is 13, the number of time-series output data is 1, there are 12 hidden layers, and 1 output layer can be observed. The time interval or delay number between input and output data was set to 5, and prediction results were obtained.

For Turkey, after selecting the 'NARX Neural Network' application with Matlab's 'ntstool,' the number of time-series input data used is 11, the number of time-series output data is 1, there are 10 hidden layers, and 1 output layer can be observed. The time interval or delay number between input and output data was set to 2, and prediction results were obtained.

In the study conducted for the USA, when the number of hidden layers is chosen as 10 and the delay number is 2, an R value of 0.96974 is obtained, but the desired value is not achieved with an R value of 0.67255 for the test. However, different hidden layers and delay numbers can be tried. In this way, both training and test R values can be examined, and hidden layer and delay values can be selected for the research. Sample operations for different hidden layers and delay values can be seen in Table 9 for the USA. Of course, with repeated trials using similar data, different R values can be obtained, so the study can be concluded when the most suitable values are determined. In this study, for the USA, 15 hidden layers and 5 delay values were selected, and for Turkey, 10 hidden layer numbers and 2 delay numbers were preferred.

TABLE IX
THE R VALUES OBTAİNED FOR THE TRAİNİNG AND TESTİNG OF THE NARX BAYESİAN MODEL USED WİTH THE ANN 'NTSTOOL' TOOL FOR THE USA

USA		R Values		
Hidden Layers	Delay Numbers (d)	Training	Test	Process Completion Reason
10	2	0.98882	0.91281	Mu Coefficient
10	5	0.96774	0.92773	Mu Coefficient
14	2	0.99650	0.92802	Mu Coefficient
14	5	0.97995	0.87176	Mu Coefficient
15	**5**	**0.99616**	**0.93254**	Mu Coefficient
15	2	0.96987	0.67255	Mu Coefficient
16	2	1.00000	0.86903	Mu Coefficient
16	5	0.98008	0.81632	Mu Coefficient
20	2	0.99972	0.96141	Mu Coefficient
20	**5**	**1.00000**	**0.99525**	Mu Coefficient

In Figure 11 for the USA and Figure 12 for Turkey, information regarding the training algorithms and processes is displayed. During the neural network training, the training concluded when the 'Mu' coefficient indicated that the weights in neurons had achieved their optimal performance and further improvement was not possible.

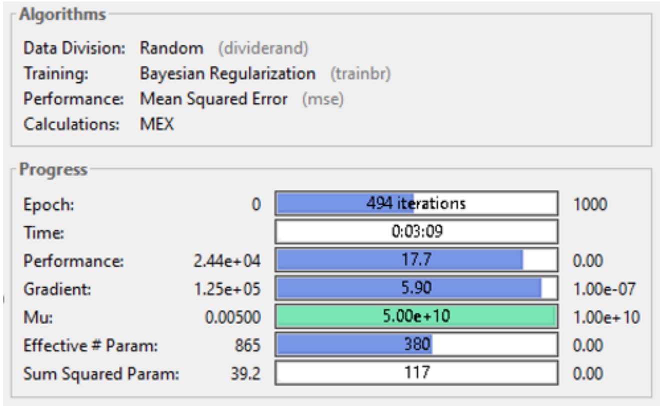

Figure 11. Information about the training algorithms and processes for the USA

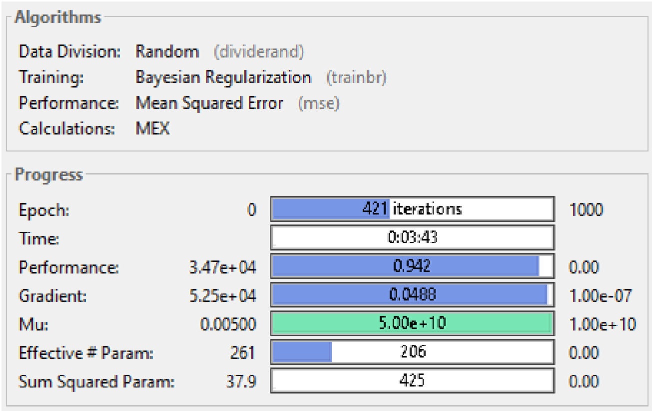

Figure 12. Information about the training algorithms and processes for the Turkey

The training process with “Artificial Neural Network” involves performing the training with 75% of the data, validation with 15% of the data, and testing with the remaining 15% of the data. The regression "R" value measures the correlation between the output data and the target data. A value close to 1 indicates a strong relationship between the two variables, while a value close to 0 indicates a random relationship. Figures 13 and 14 show the regression values obtained from the correlation between the output data and the target data used for training and testing.

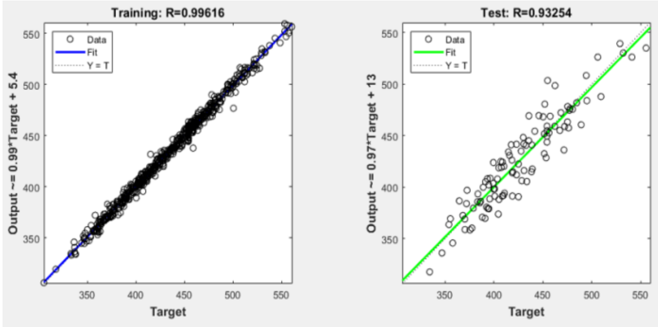

Figure 13. Regression values after training and testing using the NARX Neural Network model for the USA

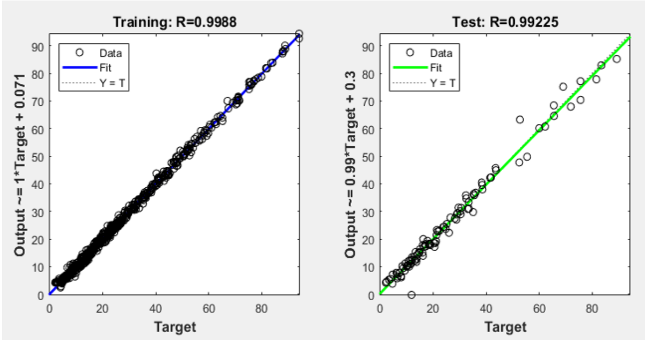

Figure 14. Regression values after training and testing the NARX neural network model for Turkey

The R values obtained from the Artificial Neural Network (ANN) modeling conducted using all the data for the USA and Turkey, along with the greenhouse gas emission predictions, are presented comparatively for both the training and testing processes in Table 10.

TABLE X
THE R-VALUES OBTAINED FOR BOTH TRAINING AND TESTING PHASES FROM THE GREENHOUSE GAS EMISSION DATA PREDICTION USING ALL AVAILABLE DATA FOR THE USA AND TURKEY

Country	Definition	R values
USA	R (Training)	0.99616
	R (Test)	0.93254
Turkey	R (Training)	0.9968
	R (Test)	0.99225

4.4. Comparison of Greenhouse Gas Emission Results between ANN and LSTM

Beginning in January 2023, predictive data was acquired using the LSTM algorithm in deep learning. This predictive dataset, spanning 63 months from January 2023 onwards, was subsequently integrated with the existing dataset. For the artificial neural network (ANN), greenhouse gas emission data were employed as output data within the "ntstool" environment, while all other data variables served as input for predictive modeling.

Comparing the predictions generated by the ANN-NARX model to the actual greenhouse gas emission data revealed close correspondence. These findings are visually represented in Figure 15 for the United States and Figure 16 for Turkey, with a focus on the data pertaining to the year 2010.

Additionally, Table 11 is provided, which includes error ratios depicting the comparison between the predictions generated by the ANN-NARX model and the actual greenhouse gas emission data. Specifically, for the year 2010, the error ratios between the actual values and the predictions obtained by the ANN-NARX model are also depicted.

TABLE XI
MONTHLY GREENHOUSE GAS EMISSION REAL VALUES AND ANN-NARX PREDICTIONS (2010) FOR THE UNITED STATES AND TURKEY IN 'MTON CO_2E' UNITS WITH PERCENTAGE ERRORS

	USA			Turkey		
Month (2010)	Actual Data	ANN-NARX	% Error	Actual Data	ANN-NARX	% Error
1	524,19	519,35	-0,92	42,26	43,10	-1,98
2	471,41	465,67	-1,22	54,94	54,75	0,35
3	469,02	469,80	0,17	46,49	46,85	-0,77
4	420,42	421,30	0,21	29,59	29,37	0,72
5	435,59	434,07	-0,35	16,91	17,20	-1,76
6	457,36	449,80	-1,65	38,04	37,32	1,88
7	484,43	507,67	4,80	50,72	50,12	1,17
8	490,64	485,72	-1,00	63,40	64,12	-1,14
9	441,76	448,68	1,57	33,81	34,33	-1,52
10	427,17	438,67	2,69	16,91	16,04	5,13
11	444,01	440,35	-0,82	8,45	8,45	0,08
12	527,56	515,03	-2,37	21,13	19,19	9,18

TABLE XII
MONTHLY GREENHOUSE GAS EMISSION LSTM AND ANN-NARX PREDICTIONS (2025) FOR THE UNITED STATES AND TURKEY IN 'MTON CO_2E' UNITS WITH PERCENTAGE DIFFERENCES

	USA			Turkey		
Month (2025)	LSTM	ANN-NARX	Percentage Difference	LSTM	ANN-NARX	Percentage Difference
1	434,2	430,4	-0,87	18,3	18,924	-3,42
2	437,2	435,2	-0,46	7,539	9,5837	-27,12
3	459,5	457,6	-0,41	26,08	26,309	-0,89
4	480,1	478,3	-0,39	51,96	53,095	-2,19
5	436,6	442,5	1,35	75,24	76,909	-2,22
6	437,9	464,5	6,07	50,57	50,838	-0,54
7	407	407,1	0,04	32,53	30,701	5,62
8	386,8	384,7	-0,53	19,81	20,536	-3,65
9	378,1	396,8	4,94	43,07	43,008	0,14
10	390,2	390,2	0,02	70,68	70,178	0,72
11	386,3	387,7	0,37	83,5	83,717	-0,26
12	394,7	395,5	0,22	38,75	38,313	1,12

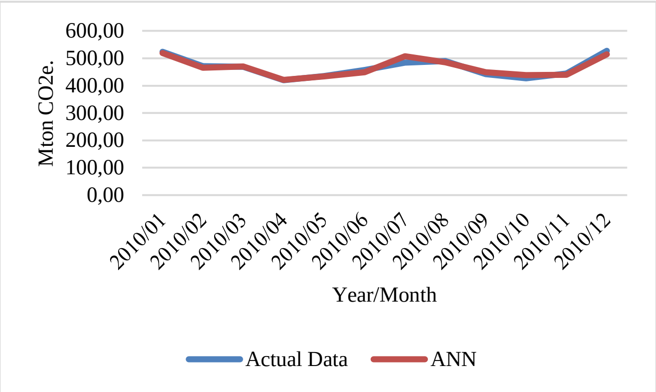

Figure 15. Comparison of actual and estimated greenhouse gas emission data for the United States by months for the year 2010, both before and after the ANN - NARX mode

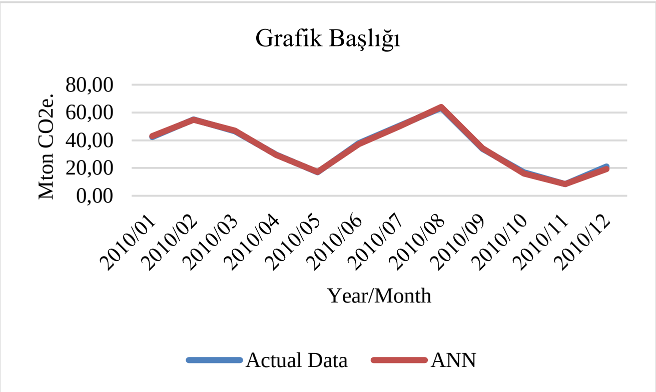

Figure 16. Comparison of actual and estimated greenhouse gas emission data for Turkey by months for the year 2010, both before and after the ANN - NARX mode

The modeling process, which involved incorporating predictive data from various sources into the ANN NARX model, resulted in greenhouse gas emission predictions that closely align with future greenhouse gas emission data obtained through the Deep Learning LSTM algorithm. When comparing the predictive data for the year 2025, as an example, the similarities between the two approaches are evident. This comparison is illustrated in Figure 15 for the United States and Figure 16 for Turkey. Additionally, in Table 12, the percentage differences between LSTM and ANN-NARX predictions can be observed.

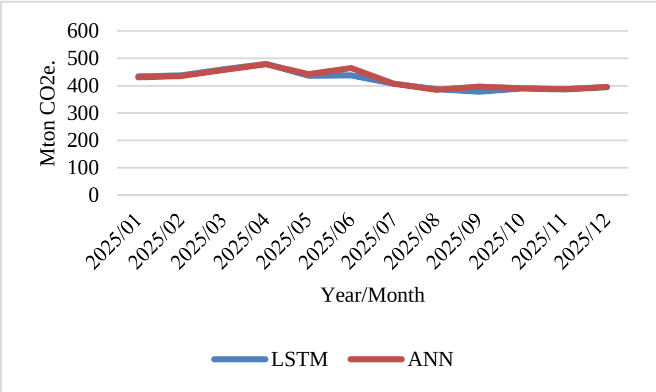

Figure 17. Comparison of Estimated Data for the Months of 2025 for the USA, Obtained with Deep Learning - LSTM Algorithm (Blue Lines) and Estimated Data for the USA Obtained with ANN Using "ntstool" (Red Line)

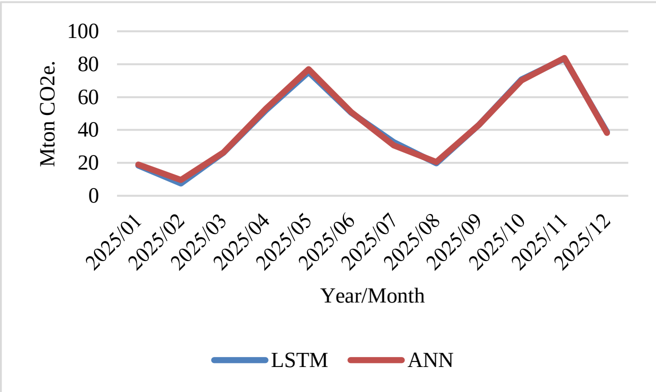

Figure 18. Comparison of Estimated Data for the Months of 2025 for Turkey, Obtained with Deep Learning - LSTM Algorithm (Blue Lines) and Estimated Data for Turkey Obtained with ANN Using "ntstool" (Red Line)

When comparing the predicted data obtained from the LSTM algorithm and Deep Learning method for the future 63 months, with the input data obtained using "ntstool" in the ANN model, it can be observed from the graph below that there is a clear relationship between the input data and the Greenhouse Gas Emission.

The future prediction data obtained through LSTM algorithm and Deep Learning has been compared with the input data obtained through Artificial Neural Network (ANN) using "ntstool". Based on this comparison, it can be observed that a clear relationship can be established between the input data and the Greenhouse Gas Emissions. In Table 13, a comparison and similarity between the annual actual greenhouse gas emission values and the estimated values, along with the corresponding percentage errors, obtained through the ANN-NARX model for the United States and Turkey from 2000 up to 2023 can be observed.

TABLE XIII
GREENHOUSE GAS EMISSION REAL VALUES AND ANN-NARX PREDICTIONS (2000-2022) FOR THE UNITED STATES AND TURKEY IN 'MTON CO_2E' UNITS

	USA			Turkey		
Year	Real Values	ANN	Percentage Error	Real Values	ANN	Percentage Error
2000	5889	5896	0,13	321,7	318,9	-0,87
2001	5778	5810	0,55	300	301,2	0,41
2002	5820	5812	-0,15	306	313,6	2,51
2003	5886	5881	-0,10	319,4	318,7	-0,23
2004	5994	5986	-0,12	323,7	320	-1,12
2005	6007	5988	-0,32	335	336,9	0,57
2006	5929	5969	0,67	370,5	370,3	-0,06
2007	6016	6004	-0,18	399,9	396,5	-0,84
2008	5823	5820	-0,05	398,6	397,1	-0,37
2009	5404	5476	1,33	406,3	411,6	1,30
2010	5594	5596	0,04	422,7	420,9	-0,43
2011	5455	5461	0,12	447,1	459,1	2,68
2012	5236	5323	1,65	479,1	467,9	-2,33
2013	5359	5360	0,02	476,9	475	-0,40
2014	5414	5433	0,35	503,7	495,7	-1,59
2015	5262	5222	-0,76	518,4	514,9	-0,67
2016	5169	5108	-1,17	546,2	546,3	0,03
2017	5131	5161	0,57	591,8	594,9	0,52
2018	5278	5241	-0,69	592,6	577,3	-2,59
2019	5147	5089	-1,12	585,3	582,3	-0,51
2020	4580	4629	1,08	585,6	598,9	2,28
2021	4903	4853	-1,02	627,1	623,1	-0,64
2022	4892	4865	-0,55	627,1	632,9	0,92

In Table 14, you can observe a comparison and proximity between the annual greenhouse gas emission values, along with percentage errors, for the United States and Turkey, starting from 2023 up to 2028, in relation to the ANN-NARX model and LSTM estimated values.

TABLE XIV
GREENHOUSE GAS EMISSION LSTM AND ANN-NARX PREDICTIONS (2023-2027) FOR THE UNITED STATES AND TURKEY IN 'MTON CO_2E' UNITS

	USA			Turkey		
Year	LSTM	ANN	Percentage Difference	LSTM	ANN	Percentage Difference
2023	5136	5143	0,13	522,7	520,8	-0,36
2024	5248	5183	-1,23	518,9	516,1	-0,55
2025	5028	5071	0,84	518	522,1	0,79
2026	4761	4775	0,29	541,5	532,1	-1,74
2027	5034	4985	-0,97	547,2	544,5	-0,48

For both the United States and Turkey, the predictive greenhouse gas emission values obtained through the ANN NARX model using the "ntstool" tool are depicted in Figure 19 for 5-year intervals, spanning from 1970 to 2025.

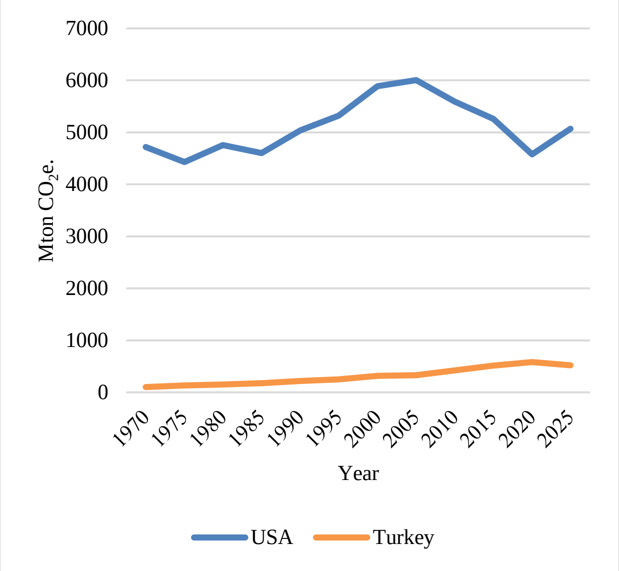

Figure 19. Actual Greenhouse Gas Emission Values and Predictive Values in "Mton CO_2e" for the United States and Turkey

During the research process, time series data were created by separately evaluating various data for each country, including greenhouse gas emissions, economic and financial conditions, primary and renewable energy supplies, population, and afforestation, in addition to factors like land use. Compared to previous studies, this research has introduced a multifactorial approach by incorporating a broader range of data, such as economic and financial indicators, alongside factors like afforestation.

5. RESULTS AND RECOMMENDATIONS

During the research process, time series data were created by separately evaluating various data for each country, including greenhouse gas emissions, economic and financial conditions, primary and renewable energy supplies, population, and afforestation, in addition to factors like land use. Compared to previous studies, this research has introduced a multifactorial approach by incorporating a broader range of data, such as economic and financial indicators, alongside factors like afforestation.

Upon examining the data from a methodological perspective, the utilization of deep learning methods, specifically LSTM, and the hybrid CNN-RNN approach, has yielded successful prediction results. Furthermore, the use of the NARX model with the MATLAB "ntstool" tool, where correlation values are close to 1, demonstrates the effectiveness of this study. When the predicted greenhouse gas emission values are compared with real data, it becomes evident that accurate predictions have been achieved.

Moreover, when the results are examined on a country-specific basis, it can be interpreted that Turkey experienced a reduction in greenhouse gas emissions, particularly during the pandemic period that began in 2019. This reduction can serve as an indicator of global economic challenges. In the case of the United States, the analysis of future predictions reveals that while there has been a decrease in greenhouse gas production compared to the 2000s, it has not fallen below the levels observed in the 1990s. Consequently, within the scope of this study, it is apparent that both the United States and Turkey have not reached the greenhouse gas production levels of the 1990s. This suggests a need for increased efforts in addressing climate change. Furthermore, it can be inferred that the reductions in greenhouse gas emissions in these countries have led to heightened awareness regarding global warming.

To achieve more comprehensive results in the analysis and prediction of climate change and greenhouse gas emissions, several recommendations can be made. In order to more accurately predict future greenhouse gas emissions, richer sources of data can be employed compared to previous research efforts. For instance, a broader range of parameters and data categories, including climate data, economic and financial indicators, population statistics, energy consumption data, urbanization rates, migration patterns, forest areas, environmental policies, and investments in renewable energy technologies, can be incorporated to construct a more comprehensive model. Given the success of advanced artificial intelligence techniques like "Deep Learning" and similar artificial neural network algorithms, it is reasonable to expect improved results with advanced AI techniques. Additionally, analyses based on various future scenarios can be conducted to formulate effective policies for greenhouse gas emissions. These analyses, rooted in machine learning, can provide policymakers with more efficient strategies for addressing climate change.

The increasing world population is increasing the demand for the industrial sector. Consequently, population growth and industrial demands make energy consumption essential. However, it is evident that primary energy sources contribute to greenhouse gas emissions and therefore are the main cause of global warming. Therefore, in order to prevent a global catastrophe, it is necessary to move away from primary energy sources as much as possible and shift towards renewable energy sources. The use of renewable energy sources seems achievable through increasing the utilization of sources such as hydropower, solar power, wind power, biomass, geothermal, wave, tidal, and hydrogen. By utilizing these sources, the need for renewable energy can be met by moving away from non-renewable energy sources.

REFERENCES

[1] KORKMAZ, K., Küresel Isınma ve Tarımsal Uygulamalara Etkisi. Alatarım dergisi, 2007, 6.2: 43-49.

[2] Levinson, D. (2020). Logistic Curve Models of CO2 Accumulation. Findings.

[3] Ayyıldız, B. (2013). Ekolojik ekonomi yaklaşımı ile Türkiye'de çevresel etkinlik analizi (Master's thesis, Gaziosmanpaşa Üniversitesi, Fen Bilimleri Enstitüsü).

[4] Şahin Ü., Tör O. B., Teimourzadeh S., Demirkol K., Künar A., Voyvoda E., Yeldan E., 2022, TÜRKİYE'NİN KARBONSUZLAŞMA YOL HARİTASI: 2050'DE NET SIFIR

[5] Wikimedia Foundation, Inc., 2023, Access URL: https://en.wikipedia.org/wiki/Charles_David_Keeling, [Accessed: Feb. 15,2023]

[6] DİKEN, G. (2020). Antropojenik iklim değişikliğinin balıkçılık ve su ürünleri üzerine etki ve yönetim stratejilerine genel bir bakış. Journal of Anatolian Environmental and Animal Sciences, 5(3), 295-303.

[7] United Nations Resmi Web Sitesi, 2022, Access URL: https://www.un.org/en/climatechange/paris-agreement , [Accessed: Jun. 08, 2022]

[8] Aydın, S. G. ve Aydoğdu, G., 2022, Makine Öğrenmesi Algoritmaları Kullanılarak Türkiye ve AB Ülkelerinin CO2 Emisyonlarının Tahmini, Avrupa Bilim ve Teknoloji Dergisi, (37), 42-46.

[9] Uzlu, E., 2021, Estimates of Greenhouse Gas Emission in Turkey with Grey Wolf Optimizer Algorithm-Optimized Artificial Neural Networks, Neural Computing and Applications, 33(20), 13567-13585.

[10] Acheampong, A. O. and Boateng, E. B., 2019, Modelling carbon emission intensity: Application of artificial neural network, Journal of Cleaner Production, 225, 833-856.

[11] Ali, N., Assad, M. E. H., Fard, H. F., Jourdehi, B. A., Mahariq, I. and Al-Shabi, M. A., 2022, CO2 Emission Modeling of Countries in Southeast of Europe by Using Artificial Neural Network, In Sensing for Agriculture and Food Quality and Safety XIV, Vol. 12120, 100-104.

[12] Komeili Birjandi, A., Fahim Alavi, M., Salem, M., Assad, M. E. H. and Prabaharan, N., 2022, Modeling Carbon Dioxide Emission of Countries in Southeast of Asia by Applying Artificial Neural Network, International Journal of Low-Carbon Technologies, 17, 321-326.

[13] European Union, Official Website, Access URL: https://edgar.jrc.ec.europa.eu/dataset_ghg70#p3, [Accessed: Feb. 24, 2023]

[14] UNDP (United Nations Expanded Programme), 2023, Access URL: https://hdr.undp.org/data-center/human-development-index#/indicies/HDI, [Accessed: Feb. 17, 2023]

[15] Organisation for Economic Co-operation and Development, 2023, Access URL: https://stats.oecd.org/index.aspx?queryid=6779, [Accessed: Feb. 20, 2023]

[16] Organisation for Economic Co-operation and Development, 2023, Access URL: https://data.oecd.org/natincome/net-national-income.htm, [Accessed: Feb. 19, 2023]

[17] Birleşmiş Milletler, 2023, Access URL: https://unstats.un.org/unsd/snaama/Basic, [Accessed: Feb. 19, 2023]

[18] TUNALI, Ç. B., 2011, Uluslararası Para Fonu'nun Kredilendirme Mekanizması: Düşük Gelirli Ülkelere Yönelik Bir İnceleme. Maliye Araştırma Merkezi Konferansları, (56), 69-93.

[19] Organisation for Economic Co-operation and Development, 2023, Access URL: https://stats.oecd.org/index.aspx?queryid=6779, [Accessed: Feb. 20, 2023]

[20] Kaya, K., & Koç, E., 2015, Enerji Kaynakları-Yenilenebilir Enerji Durumu. Mühendis ve Makina, 56(668), 36-47.

[21] Organisation for Economic Co-operation and Development, 2023, Access URL: https://data.oecd.org/energy/primary-energy-supply.htm#:~:text=Primary%20energy%20supply%20is%20defined,plus%20or%20minus%20stock%20changes, [Accessed: Feb. 21, 2023]

[22] Organisation for Economic Co-operation and Development, 2023, Access URL: https://data.oecd.org/energy/renewable-energy.htm#indicator-chart, [Accessed: Feb. 21, 2023]

[23] U.S. Energy Information Administration (EIA), 2023, Access URL: https://www.eia.gov/totalenergy/data/monthly/index.php, [Accessed: Feb. 20, 2023]

[24] The World Bank, 2023, Access URL: https://www.worldbank.org/en/topic/forests/forests-area#4, [Accessed: Feb. 19, 2023]

[25] Alizadeh, M. (2011). Yapay Sinir Ağları İle Fiyat Tahmin Analizi. İstanbul Üniversitesi. Fen Bilimleri Enstitüsü, Yüksek Lisans Tezi, İstanbul, 90s.

[26] Dandil, E. & Serin, Z., 2020, Derin Sinir Ağları Kullanarak Histopatolojik Görüntülerde Meme Kanseri Tespiti, Avrupa Bilim ve Teknoloji Dergisi, 451-463.

[27] Sanchez, H., 2023, Time Series Forecasting Using Hybrid CNN – RNN, MATLAB Central File Exchange, Retrieved April 24, 2023.

[28] Alizadeh, M., 2011, Yapay Sinir Ağları İle Fiyat Tahmin Analizi, Yüksek Lisans Tezi, İstanbul Üniversitesi Fen Bilimleri Enstitüsü, İstanbul, 90s.

BIOGRAPHIES

Necmettin Sezgin graduated with a Bachelor of Science degree in Electrical and Electronics Engineering from Hacettepe University, Faculty of Engineering, in 2001. He completed his Master of Science in Electrical and Electronics Engineering at Dicle University, Graduate School of Natural Sciences, in 2003, and his PhD in the same field at İnönü University in 2011. In 2011, he joined Batman University as an Assistant Professor in the Department of Electrical and Electronics Engineering. In 2014, he was awarded the title of Associate Professor in Electrical and Electronics Engineering by the Turkish Interuniversity Board and continued his work at Batman University in the same department. In 2019, he became a Professor in the Department of Computer Engineering at Batman University, where he currently works. He has served in various editorial and peer-review roles for national and international journals. Additionally, he has held several administrative roles at the university, including Acting Dean, Vice Dean, Founding Department Head, Chair of the Department, Senate Member, University Board Member, and Faculty Board Member. His research interests include electronics, biomedical engineering, and signal processing.

Serkan Ertuğrul graduated with a Bachelor of Science in Electronics Engineering from Istanbul University in July 2002. He later earned a second bachelor's degree in Business Administration from Anadolu University's Faculty of Business in June 2018. He obtained his Master of Science degree in Electrical and Electronics Engineering from Batman University in July 2023 and is currently pursuing his PhD in the same field at Batman University. His research interests include control theory, machine learning, deep learning, and signal processing.