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Energy Demand and CO_2 Emission Forecast Model for Turkey with Deep Learning and Machine Learning Algorithms

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***Abstract*—This study has conducted a forecast analysis of the energy demand and carbon dioxide (CO_2) emissions of Turkey, a developing country. Considering Turkey's rapidly increasing energy demand, various economic and social parameters have been used for the years 1990-2024. Both machine learning and deep learning methods have been applied, and artificial neural network (ANN), convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), and linear regression (LR) algorithms have been used for two models. The performance of these models has been assessed using various error metrics. The ANN has demonstrated the highest accuracy in modelling energy demand, achieving a coefficient of determination of 98.89 %, while the RNN has shown the best performance in modelling CO_2 emissions, with a coefficient of determination of 96.80 %. The findings have shown that the growth rates in energy demand and CO_2 emissions are high in the early years but slowed in the following years. However, it has been determined that the general trend continued to increase. The study emphasises the need for Turkey to diversify its energy sources and increase the use of renewable energy to meet its increasing energy demand. It also has concluded that accelerating efforts to achieve net zero emission targets are critical to long-term energy security and environmental sustainability.**

***Index Terms*—Energy demand; CO_2 emission; Deep learning; Machine learning; Sustainability.**

I. INTRODUCTION

Energy is one of the most critical components of social and economic development, essential for improving living standards and ensuring sustainable progress. From a broader perspective, it serves as the foundation for sustainable living and influences the future social, geographical, and economic landscape. Global energy demand fluctuates based on various factors, including demographic trends, economic growth, technological advances, employment rates, energy prices, and climatic conditions. In 2023, worldwide energy consumption increased by a record 2.5 % to 620 EJ [1].

One of the crucial goals of the energy system is to increase the share of renewable energy sources in energy production and to promote a clean environment by decarbonising energy. Despite the encouragement for renewable energy investments in many countries, when examining energy consumption in 2023 by source (Fig. 1), it becomes evident that coal and natural gas remain the predominant sources. Coal and other fossil fuels account for approximately 60 % of global electricity generation. In particular, between 2022 and 2023, coal saw a 1.6 % increase, seven times higher than the average growth rate during the previous decade [1].

Although many countries have committed to reducing carbon and greenhouse gas emissions in the energy system by participating in the Paris Treaty signed in 2015 and the Kyoto Protocol in 1997, it is known that they have yet to reach the desired targets. In fact, in 2023, greenhouse gas emissions exceeded 40 $GtCO_2$, a record high, and 87 % of this value is due to fossil fuel sources [1]–[3].

Looking at the energy sector from Turkey's perspective, electricity consumption in 2023 (Fig. 1) increased by 1.2 % compared to the previous year and reached 335.2 TWh, while electricity generation reached 331.1 TWh. Of the electricity generation, 36.2 % were generated from coal, 21 % from natural gas, 19.3 % from hydraulic energy, 10.3 % from wind, 6.7 % from solar, 3.4 % from geothermal energy, and 3.2 % from other sources [4].

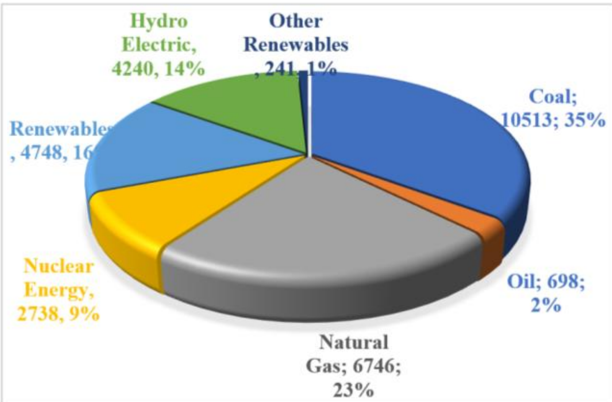

Fig. 1. Distribution of the world's energy consumption by sources.

Considering all these situations, energy management is crucial to achieving a sustainable life and a clean

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environment. It involves responsible use of resources and smooth operation of various service sectors. Accurate energy forecasting is fundamental to effective energy management. The energy consumption forecast is classified according to the period and can be divided into four categories.

Ultra-short-term electricity consumption forecasts, ranging from one minute to one hour, and short-term forecasts, covering periods from one hour to two weeks, are essential to optimise unit commitment, manage reserves, and evaluate sales or purchase contracts between various companies. Mid-term electricity consumption forecasts, which span from two weeks to three years, contribute to efficient power system operation and maintenance. Long-term forecasts, spanning three to 50 years, are used for long-term planning of the power system, helping to assess the future energy demand and energy policy of a country [5]–[8].

Research on energy demand- consumption, generation, and emission forecasting shows significant variation based on changes in input parameters, as well as differences in coverage time frames and the methods used. A summary of various studies from the literature on this topic is presented in Table I, organised according to these classifications.

This paper presents a study on the forecasting of energy demand and CO_2 emissions for Turkey, which has the fastest growing energy demand among the Organisation for Economic Co-operation and Development (OECD) countries and is second in the world after China for both electricity and natural gas demand [4]. The analysis uses data on various parameters, including population, gross domestic product, export, import, energy demand, electricity consumption per capita, and the number of motor vehicles for the years 1990 to 2024. In particular, the inclusion of motor vehicle data is significant, as it is believed to have a considerable influence on both energy demand and emissions, both of which are continuously increasing. Two separate simultaneous models have been established to estimate energy demand and CO_2 emissions. The forecasting has been carried out by using several methodologies: artificial neural network (ANN), convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), and linear regression (LR). Reliability metrics have been used to evaluate the models, including coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE). After demonstrating successful predictions, forecasting has been conducted at three different levels, low, based, and high, for the next ten years. This study is expected to play a crucial role in shaping Turkey's future energy policies and understanding its potential for emission.

TABLE I. LITERATURE REVIEW.

Ref.	**Time horizon**	**Region**	**Prediction method**	**Metric**	**Aim-Forecasting**
[9]	Yearly data 1979–2005	Turkey	ACO	RE	Energy demand
[10]	Yearly data 1981–2005	Iran	BE, PSO, and GA	RE	Energy demand
[11]	Monthly data 2008–2011	Kutubdia and Maheshkhali island	LR	GR	Energy demand
[12]	Yearly data 1970–2006	Italy	RT	EV	Energy demand, CO_2 emission, and economic growth
[13]	Monthly data 2002–2013	India region	ARIMA models	RMSE, MAE, MAPE, ME, and AICc	Energy consumption and greenhouse gas emission in pig iron production
[14]	Monthly data 2-year interval between March 2014 and February 2016	Brazilian power company	CNN and LSTM	MAE, MAPE, and MdAPE	Energy consumption
[15]	Two-month period	Ireland	LR, ANN, PSO, and DE	MAE, MSE, RMSE, and MAPE	Energy demand, wind energy, and atmospheric pollutant
[16]	Yearly data 1985–2015	China	AGA and CA	MAE, MSE, MAPE, and RMSE	Energy demand
[17]	Yearly data 1995–2010	China	GM, CES, and G-CES	MSE, MAPE, and R^2	Traffic carbon emission in transportation sector
[18]	Yearly data 1980–2019	China	CF and D-SVM	Comparison	Energy consumption structure
[19]	Fixed-Nonfixed Shiftable loads data	Rajastan	CNN, LSTM, and RNN	MSE, RMSE, and MAE	Wind and solar generation and energy consumption
[20]	Hourly data 28 different homes hourly data	British Columbia	RNN, LSTM, GRU, TST, and SAA	MAE, MAPE, and R^2	Hourly energy consumption
[21]	Yearly data 1990–2019	Canada	AR, ARIMA, ARFIMA, SARIMA, GARCH, GM, MIDAS, and SVR	RMSE, NRMSE, MAPE, MAE, and RAE	Energy demand and CO_2 emission in transportation sector
[22]	Monthly data January 2020 to January 2023	Downtown University	LSTM, RF, and GBR	RMSE, MAE, and MAPE	Energy consumption prediction for energy efficiency in educational building
[24]	Daily data	Six critical sectors in 13 countries	I-ARIMA	MAE and RMSE	Carbon emission predicting in different sectors
[25]	Daily data 2011–2012	London household	CNN	RMSE, MSE, MAE, and MAPE	Electric load

II. METHODOLOGY

There are two primary methods used in the forecasting process. The first method involves expressing the parameter to be estimated as a mathematical relationship based on previously observed physical parameters. The second method interprets various parameters through algorithms that utilise historical data sets, resulting in an algorithmic relationship. In this study, two distinct models have been developed using historical data sets: one to forecast energy demand and another to forecast CO_2 emissions. The flow diagram illustrating the energy demand forecasting study is presented in Fig. 2. The emissions demand model is similar.

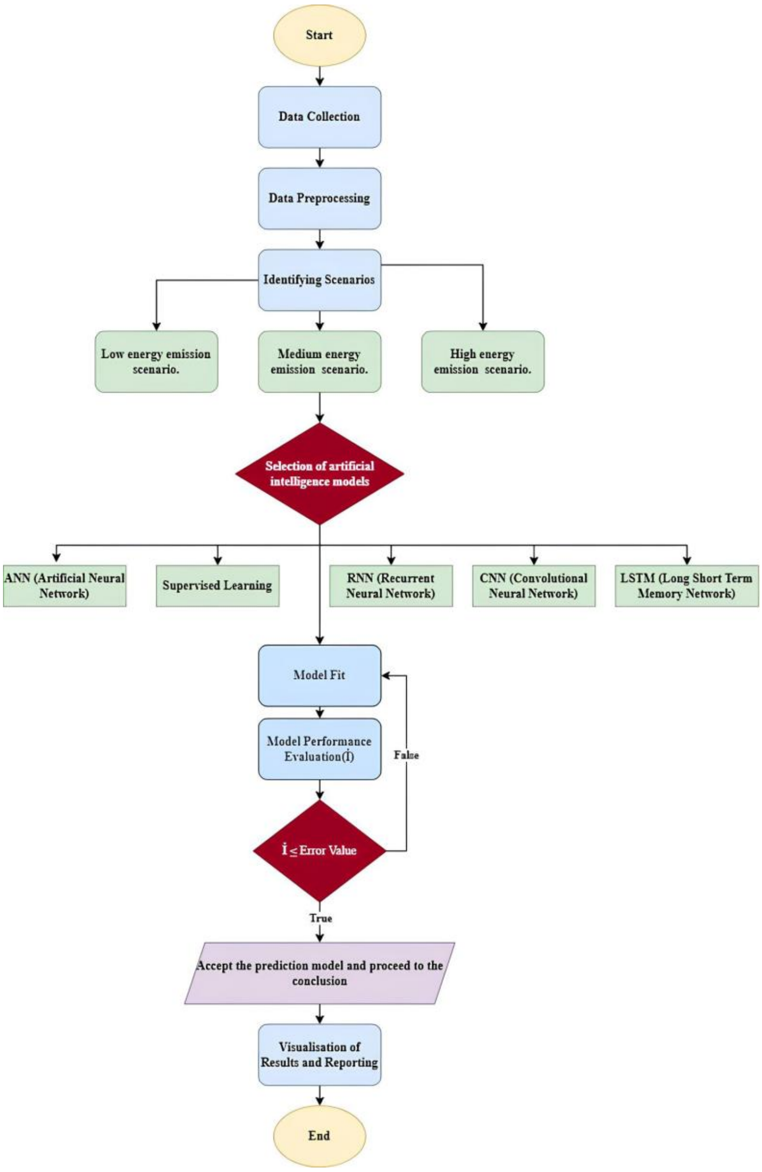

Fig. 2. The flow chart of the study.

A. Data Collection and Data Preprocessing

Various dependent and independent variables have been identified that are used to develop models to estimate energy demand and CO_2 emissions. Energy demand and CO_2 emission served as the dependent variables, while the independent variables included population, gross domestic product (GDP), exports, imports, electricity consumption per capita, and the number of motor vehicles. In the CO_2 emission model, energy demand has been included as one of the independent variables.

The data for these variables from 1990 to 2024 have been organised into a time series format. All analyses have been performed using Python software. The data set has been created with the Pandas library, and it has been cleaned by removing spaces and special characters.

To enhance the accuracy and reliability of the model, normalisation was applied to the data set. During the normalisation process, all data values have been scaled to the range of [0, 1], as described in (1)

$$x(t) = \frac{x(t) - \min(x)}{\max(x) - \min(x)} + 1, \tag{1}$$

where x(t) are the scaled data, min(x) is the minimum value of the data, max(x) is the maximum value of data, and $\widehat{x(t)}$ is the normalized value.

B. Model Definition and Methods Artificial Intelligence Used

Both machine learning and deep learning techniques have been employed for prediction, providing robust and innovative solutions. A detailed description of these methods is given below.

– Artificial Neural Network (ANN)

ANNs are mathematical models that replicate the functions of the human brain, drawing inspiration from biological neurons. An artificial neural network is made up of multiple artificial neural cells. The components of an artificial neural network cell include inputs, weights, additivity, an activation function, and the output, as illustrated in Fig. 3 [25], [26].

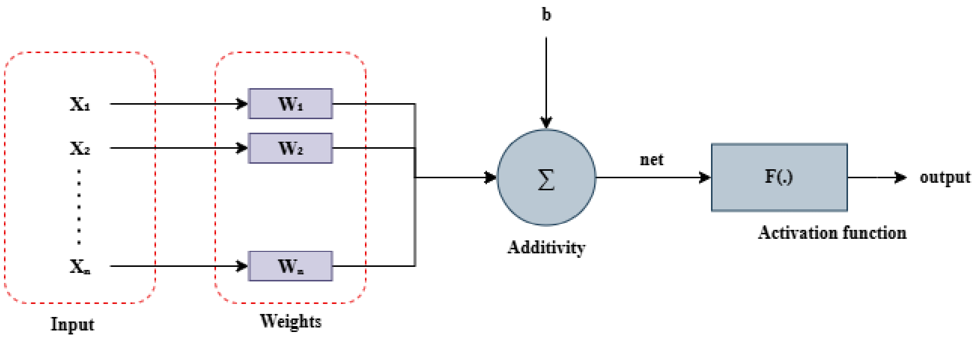

Fig. 3. The structure of ANN.

In Fig. 3, the inputs (x_1, x_2, …, x_n) refer to information coming from the external environment or other cells. These inputs are determined by the examples that the network is designed to learn. The weights (w_1, w_2, ..., w_n) represent the values that indicate the influence of the input set on the processing element. Each input is multiplied by the corresponding weight that connects it to the processing element. The results are then combined using a summation function, as expressed in (2) [25], [26]

$$net = \sum_{i=1}^{n} w_i x_i + b. \tag{2}$$

The output from the total function is processed through the activation function, resulting in the calculation of the output from the process using (3)

$$output = y = f(net) = F\left(\sum_{i=1}^{n} w_i x_i + b\right). \tag{3}$$

Activation functions vary depending on the specific problem being addressed. Commonly used functions include the sigmoid, hyperbolic tangent, maxout, and rectified linear unit (ReLu). In this study, the ReLu function has been preferred due to its resemblance to the behaviour of biological neurons and its widespread use in the literature, where it has been shown to deliver successful and efficient results. The ReLu function is defined as follows: It checks whether the input values are positive or negative. If the value is negative, the output is 0; if the value is positive, the output remains unchanged. This can be expressed in (4) [25], [26]

$$F = \max(0, x). \tag{4}$$

There are various network structures and models in artificial neural networks, which differ based on the number of layers and the method of propagation. In this study, we used a multilayer feedforward artificial neural network (ANN) and its structure is depicted in Fig. 4.

– Linear Regression Model

If the relationship between a dependent variable and one or more independent variables is linear, it is referred to as a multiple linear regression model, which can be expressed in (5)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + e, \tag{5}$$

where β_0, β_1, β_2, ..., β_k represent unknown parameters, and e denotes error term.

This method, which is widely used in the literature, relies on several assumptions:

1. Both dependent and independent variables should be quantitative, either discrete or continuous, and measured at equal intervals or on a ratio scale;
2. The dependent variable should conform to a normal distribution;
3. Independent variables must be measured without error, and there should be no multicollinearity among them;

The error terms must be independent of each other, follow a normal distribution with a mean of zero, and have equal variance [27].

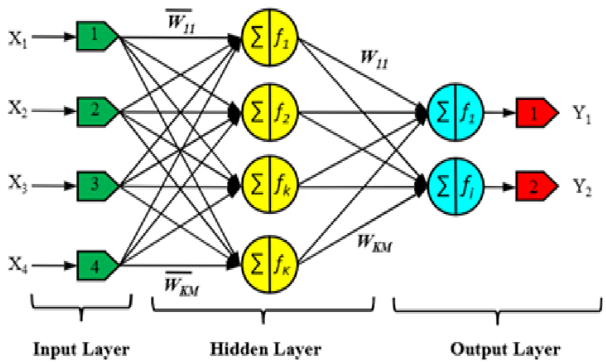

Fig. 4. Multilayer and feedforward propagation ANN.

– Convolutional Neural Networks (CNN)

CNN was developed in 1968 by Hubel and Wiesel, drawing inspiration from the visual systems of animals [28], [29]. CNN consists of convolutional, ReLu, pooling, and fully connected layers. The convolutional layer serves multiple functions, including extracting features from the input, reducing dimensionality, classifying, and applying new filters. The next layer, the rectified linear unit, acts as an activation function, generally using the ReLu function. The pooling layer increases processing speed by reducing the matrix size resulting from convolution. In the final layer, the model determines the object category based on the extracted features. These layers are typically organised into groups, with properties of two-dimensional arrays attained through their repetition. In regression problems, a regression layer can be added at the end of the model to predict continuous data [28], [29].

– Recurrent Neural Network (RNN)

RNN is a deep learning model designed to process sequential data. Unlike traditional neural networks, where each input is considered independent, RNNs recognise that inputs are related to each other. This means that the current input data are evaluated in conjunction with previous input, and the output from one step becomes the input from the next step. The outputs are generated based on the input values and an error value is calculated by comparing the outputs with the expected results [30].

An RNN consists of a single layer that stores state information generated by the feedforward network and reintroduces the input information back into the network. In other words, an RNN has a memory that retains previous computations. A diagram illustrating the structure of an RNN is provided in Fig. 5 [29]–[31].

Consider a sequence $[x_1, x_2, x_3, ..., x_k]$, where each $x_i \in R_d$. k denotes the length of the sequence. An RNN generates a hidden state sequence at each time step, represented as $[h_1, h_2, h_3, ..., h_k]$. The hidden state at each step is determined by the current input and the previous hidden state, as illustrated in (6)

$$h(t) = f(x_t, h_{t-1}). \tag{6}$$

The output value derived from this structure is determined using (7) [29]–[31]

$$y_t = w_{hy} h_t. \tag{7}$$

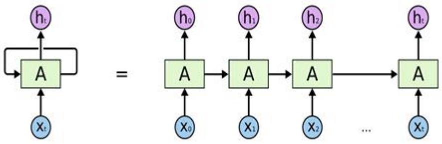

Fig. 5. The structure of RNN.

– Long Short-Term Memory (LSTM)

LSTM networks are a type of deep learning model developed by Sepp Hochreiter and Jürgen Schmidhuber in 1997 [29]–[31]. The LSTM architecture consists of four key components, as illustrated in Fig. 6. In the figure, the input gate (I) transmits the input data. The forget gate (F) determines how much data from the previous block will be retained in memory and how much will be discarded. Candidate memory (C) facilitates the generation of new information. The output gate (O) calculates and transmits the output data. Gates utilise sigmoid functions to produce outputs in the range of [0, 1], and hyperbolic tangent functions to yield outputs in the range of [-1, 1] [29]–[31].

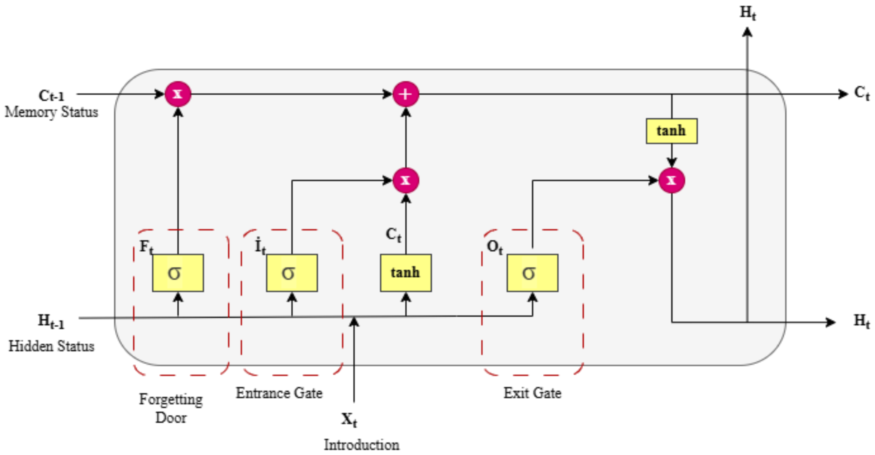

Fig. 6. The LSTM architecture.

The equations that describe the functioning mechanism within these layers are provided below:

$$i(t) = \sigma(w_i x_t + w_{hi} h_{t-1} + w_{ci} c_{t-1} + b_i), \tag{8}$$

$$f(t) = \sigma\left(w_{xf} x_t + w_{hf} h_{t-1} + w_{cf} c_{t-1} + b_f\right), \tag{9}$$

$$(t) = f(t) \odot c_{t-1} + i_t \tanh(w_{xc} x_t + w_{hc} h_{t-1} + b_c), \tag{10}$$

$$o(t) = \sigma(w_{xo} x_t + w_{ho} h_{t-1} + w_{co} c_t + b_o), \tag{11}$$

$$h(t) = o(t) \odot \tanh(c_t), \tag{12}$$

where $i(t)$, f(t), and $o(t)$ represent the input layer, the forgetting layer, and the output layer, respectively, $c(t)$ and $h(t)$ denote the cell state and hidden state values, $x(t)$ is the input vector at t-time, σ is the sigmoid function, w is the weight matrix, and b is the bias vector [28]–[31].

C. Performance Evolution

Several error metrics, including MAE, MSE, RMSE, and R^2, have been used to evaluate performance. The corresponding formulas for these metrics are presented in (13)–(16):

$$MAE = \sum_{i=1}^{n} \frac{|y_i - y_i|}{n}, \tag{13}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_i)^2, \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y_i)^2}{n}}, \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_\imath\right)^2}{\left(y_i - y_\imath\right)^2}, \qquad (16)$$

where y_i and $\hat{y}_\imath$ represent actual data and estimated data, respectively and *n* is the number of data.

D. Predict Model

Three scenarios are determined: low, basic, and high. The basic scenario reflects the values derived from our models based on historical data and current economic parameters. The low scenario, which assumes a 0.75 % growth rate, represents a situation where economic growth is slow, limiting increases in energy demand and emissions. Conversely, the high scenario, with a growth rate of 1.25 %, predicts rapid economic growth, leading to significant increases in energy demand and CO_2 emissions.

III. RESULTS AND DISCUSSION

The data set utilised to estimate energy demand and CO_2 emissions spans 35 years, covering the period from 1990 to 2024, as presented in Table II. The data set was divided into training and test sets in an 80 % and 20 % ratio, respectively. Namely, the data set from 1990 to 2017 has been used for training, while the data from 2018 to 2024 has been designated for testing. The energy demand and CO_2 emission estimation model has been developed using various machine learning and deep learning techniques, including ANN, CNN, RNN, LSTM, and LR. Each of these models has distinct advantages in terms of different data structures and forecasting needs. A summary of these models is presented in Fig. 7.

TABLE II. THE DATA SET UTILISED FOR FORECASTING ENERGY DEMAND AND CO2 EMISSIONS.

Year	**Population (10^6)**	**GDP (10^9 \$)**	**Export (10^9 \$)**	**Import (10^9 \$)**	**Energy Demand (TWh)**	**CO_2 (Mt)**	**Electricity Consumption per capita (kWh)**	**The number of motor vehicles (10^6)**
1990	54.3	151	13.0	23.1	50.13	154.1	1.1	5.43
1991	55.3	151	13.6	21.1	53.0	160.6	1.1	5.53
1992	56.3	159	14.7	24.4	58.0	166.7	1.2	5.63
1993	57.3	180	15.3	29.4	63.0	173.8	1.3	5.73
1994	58.3	131	18.1	23.4	66.0	170.1	1.5	5.83
1995	59.3	169	21.6	35.8	72.0	184.1	1.5	5.93
1996	60.3	181	23.2	42.5	79.0	202.5	1.6	6.03
1997	61.3	190	26.3	48.7	87.0	214.9	1.7	6.13
1998	62.2	276	26.9	45.9	93.0	215.0	1.7	6.22
1999	63.2	256	26.6	40.7	97.0	210.7	1.8	6.32
2000	64.1	274	27.8	54.5	105	232.4	1.9	6.41
2001	65.1	202	31.3	41.4	104	216.3	1.9	6.51
2002	66.0	240	36.1	51.6	109	223.7	1.9	10.07
2003	66.9	315	47.3	69.3	117	239.2	1.9	10.13
2004	67.8	409	63.2	97.3	127	247.2	2.0	13.42
2005	68.7	506	73.5	117.0	137	267.0	2.2	14.34
2006	69.6	557	85.5	139.0	150	284.6	2.4	15.30
2007	70.5	681	107.0	170.0	163	315.6	2.5	16.14
2008	71.3	770	132.0	202.0	171	311.7	2.5	16.84
2009	72.2	649	102.0	141.0	165	317.5	2.7	17.23
2010	73.2	777	114.0	186.0	210.0	317.6	2.8	18.03
2011	74.2	839	135.0	241.0	230.0	343.0	2.9	19.15
2012	75.3	881	152.0	237.0	242.0	357.4	3.1	20.38
2013	76.6	958	161.0	261.0	246.0	349.2	3.2	21.53
2014	78.1	939	167.0	251.0	257.0	365.7	3.2	22.24
2015	79.6	864	151.0	214.0	266.0	386.3	3.3	23.24
2016	81.0	870	149.0	202.0	279.0	404.6	3.4	24.41
2017	82.1	859	164.0	239.0	297.0	429.4	3.4	25.36
2018	82.8	778	177.0	231.0	304.0	422.1	3.5	26.11
2019	83.5	760	181.0	210.0	303.0	404.3	3.6	26.59
2020	83.7	776	190.0	219.0	310.0	414.4	3.2	24.21
2021	84.7	815	225.0	271.0	327.0	417.1	3.6	25.17
2022	85.3	905	254.0	298.0	325.0	422.8	3.9	26.20
2023	85.7	905	265.0	310.0	323.0	420.3	3.9	27.26

In general, for methods other than linear regression, the layer consists of 64 neurons. The ReLU activation function is utilised, and the time steps are processed sequentially. Following this, the dense layer contains 32 neurons, which helps to reduce the dimensionality of the features. Finally, the output layer consists of a single neuron, representing either energy demand or CO_2 emissions. A clear comparison between the actual energy demand values and the forecasted values produced by the methods proposed in this study is shown in Fig. 8. The error metric values found for the evaluation of this model are given in Table III.

The findings in Fig. 8 and Table III indicate that the best performing method in the energy demand model is the ANN, which achieved a coefficient of determination of 0.9889. The

LSTM model follows closely behind. In contrast, the LR method showed the lowest performance. The comparison of the actual values for the CO_2 emission model with the estimated values by the methods used is given in Fig. 9, and the error metrics calculated in the evaluation of this model are listed in Table IV.

```
Layer (type)                 Output Shape              Param #
================================================================
dense (Dense)                (None, 32)                256

dense_1 (Dense)              (None, 16)                528

dense_2 (Dense)              (None, 1)                 17

================================================================
Total params: 801 (3.13 KB)
Trainable params: 801 (3.13 KB)
Non-trainable params: 0 (0.00 Byte)
```

(a)

```
Layer (type)                 Output Shape              Param #
================================================================
conv1d (Conv1D)              (None, 6, 64)             192

batch_normalization (Batch   (None, 6, 64)             256
Normalization)

conv1d_1 (Conv1D)            (None, 5, 32)             4128

batch_normalization_1 (Bat   (None, 5, 32)             128
chNormalization)

dropout (Dropout)            (None, 5, 32)             0

flatten (Flatten)            (None, 160)               0

dense (Dense)                (None, 16)                2576

dense_1 (Dense)              (None, 1)                 17

================================================================
Total params: 7297 (28.50 KB)
Trainable params: 7105 (27.75 KB)
Non-trainable params: 192 (768.00 Byte)
```

(b)

```
Layer (type)                 Output Shape              Param #
================================================================
simple_rnn (SimpleRNN)       (None, 50)                2900

dense (Dense)                (None, 1)                 51

================================================================
Total params: 2951 (11.53 KB)
Trainable params: 2951 (11.53 KB)
Non-trainable params: 0 (0.00 Byte)
```

(c)

```
Layer (type)                 Output Shape              Param #
================================================================
lstm (LSTM)                  (None, 50)                11600

dense (Dense)                (None, 1)                 51

================================================================
Total params: 11651 (45.51 KB)
Trainable params: 11651 (45.51 KB)
Non-trainable params: 0 (0.00 Byte)
```

(d)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Demand (GWh)   R-squared:                       0.968
Model:                            OLS   Adj. R-squared:                  0.967
Method:                 Least Squares   F-statistic:                     983.0
Date:                Thu, 19 Dec 2024   Prob (F-statistic):           1.35e-25
Time:                        22:14:19   Log-Likelihood:                -144.19
No. Observations:                  34   AIC:                             292.4
Df Residuals:                      32   BIC:                             295.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -1.888e+04    607.720    -31.062      0.000   -2.01e+04   -1.76e+04
Year           9.4958      0.303     31.353      0.000       8.879      10.113
==============================================================================
Omnibus:                        3.184   Durbin-Watson:                   0.266
Prob(Omnibus):                  0.204   Jarque-Bera (JB):                1.924
Skew:                          -0.344   Prob(JB):                        0.382
Kurtosis:                       2.060   Cond. No.                     4.10e+05
==============================================================================
```

(e)

Fig. 7. Comprehensive overview of the methods used: (a) ANN; (b) CNN; (c) RNN; (d) LSTM; (e) LR.

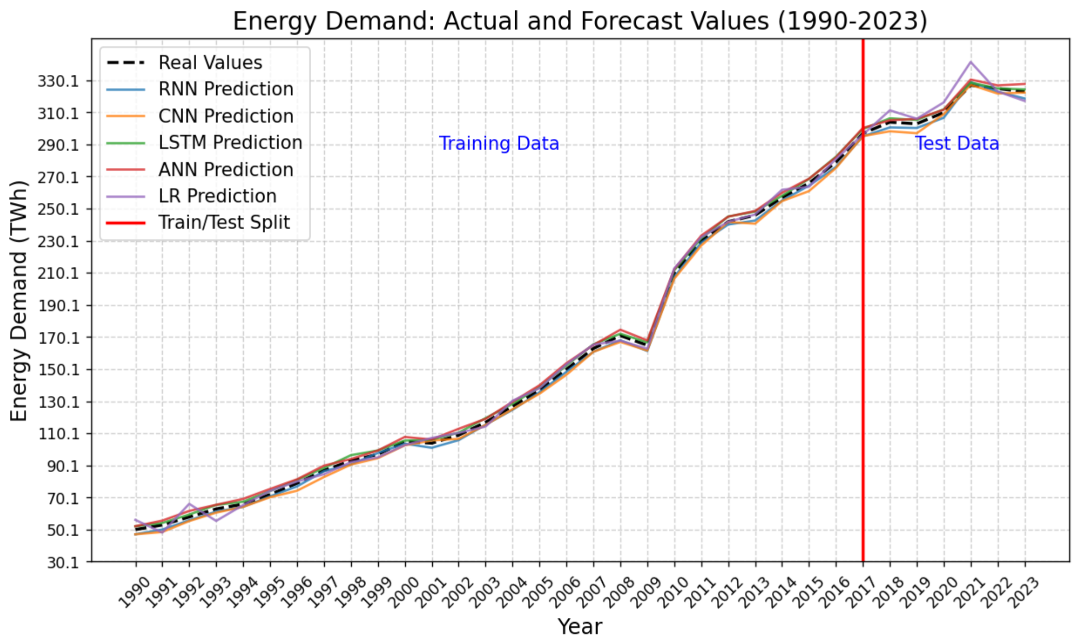

Fig. 8. Comparison of actual energy demand values and estimated energy demand values with the various methods.

TABLE III. COMPARISON OF ERROR METRICS OF ENERGY DEMAND MODELS.

	ANN	CNN	RNN	LSTM	LR
R^2	98.89 %	97.44 %	97.90 %	98.47 %	96.18 %
MSE	0.05	0.13	0.11	0.07	0.4
MAE	0.005	0.008	0.009	0.006	0.01
RMSE	0.23	0.36	0.33	0.27	0.63

TABLE IV. COMPARISON OF ERROR METRICS OF CO_2 EMISSION MODELS.

	ANN	CNN	RNN	LSTM	LR
R^2	96.44 %	95.04 %	96.80 %	96.16 %	94.10 %
MSE	0.12	0.17	0.11	0.13	0.20
MAE	0.009	0.011	0.009	0.009	0.011
RMSE	0.35	0.41	0.33	0.36	0.45

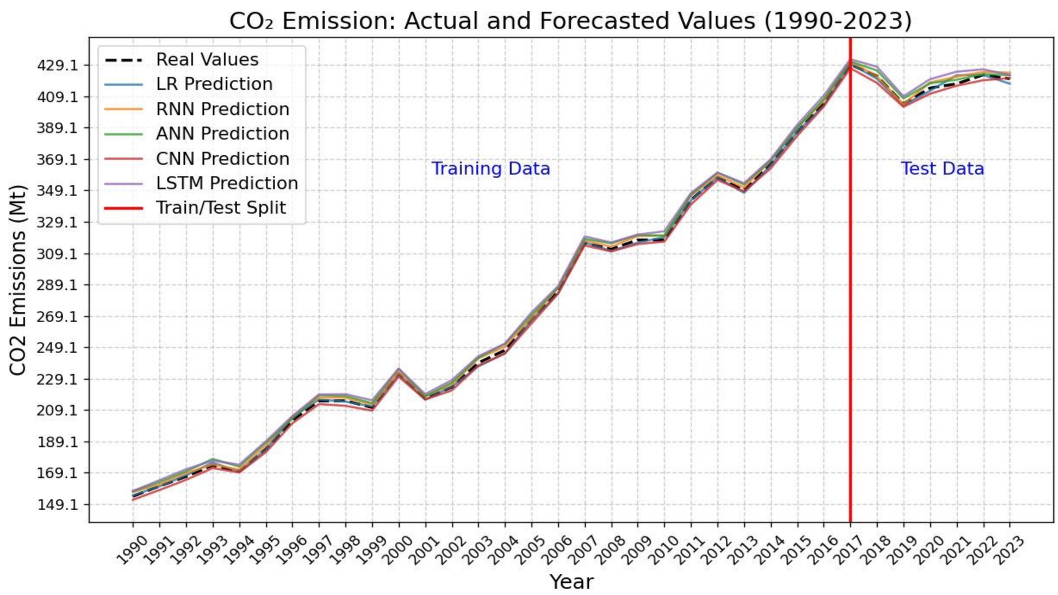

Fig. 9. The comparison of actual CO_2 emission values and estimated CO_2 emission values with the various methods.

For the emission demand model, the most suitable method has been RNN with a coefficient of determination of 96.80 %, followed by ANN with a coefficient of determination of 96.44 %. The LR method has been found to be the method with the lowest performance, as in the energy demand model. Following a detailed performance analysis of energy and emission demand models, it has been found that the model demonstrating the highest accuracy and efficiency for energy demand forecasting is ANN. Using this model, projections for the energy demand in Turkey have been made for the years 2025 to 2035, considering three different scenarios with low, basic, and high growth rates, while considering potential uncertainties in future energy demand. The results of these energy demand forecasts are illustrated in Fig. 10.

The expected energy demand for Turkey in 2025 is projected to be approximately 367 TWh, based on forecasting method, as illustrated in Fig. 11. By 2035, this demand is anticipated to rise to around 405 TWh. This increase indicates a rapid growth in energy demand, particularly in the initial years; however, the rate of increase is expected to slow over time due to the implementation of various energy efficiency and conservation initiatives.

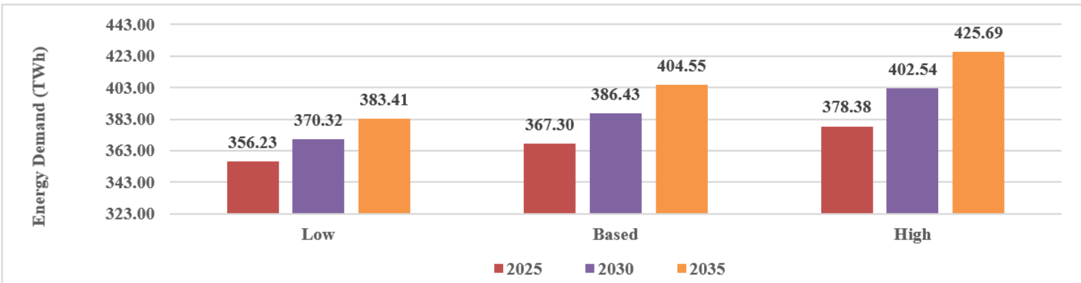

Fig. 10. Estimated energy demand values.

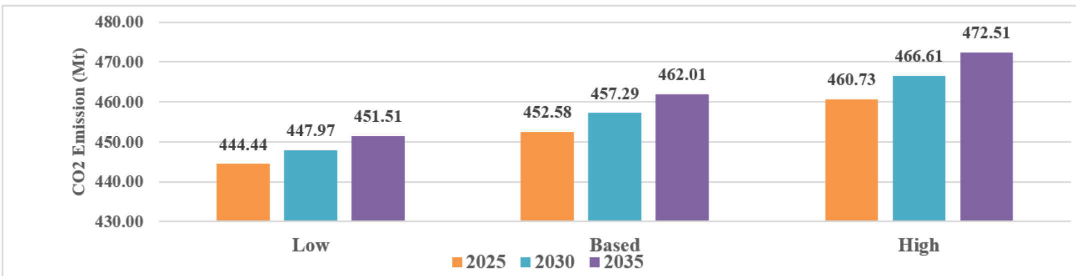

Fig. 11. Estimated CO_2 emission values.

However, it is essential to maximise the available resource potential to meet an estimated energy consumption of approximately 425 TWh by 2035, considering each scenario. Similarly, the estimation of CO_2 emission for the next ten years for Turkey has also been carried out under three different scenarios; RNN method, which provides higher accuracy for emission release estimation, has been preferred. The estimation results obtained with the relevant model are presented in Fig. 11. According to the data obtained from Fig. 11, while the CO_2 emission estimate is around 450 Mt in 2025, it is expected to reach around 460 Mt by 2035 and even increase to 473 Mt. As in the increase in energy demand, a rapid increase is observed here as well, but the rate of this increase decreases in the following years. However, emissions continue to increase. Considering environmental factors such as the European Green Deal and global warming, reaching the net zero emission target set for 2035 seems quite difficult when current emission trends are considered.

IV. CONCLUSIONS

This study has developed models to estimate Turkey's energy demand and CO_2 emissions using economic and social parameters for the years 1990 to 2024. Both machine learning and deep learning algorithms have been effectively utilised to create these models. The performance of the models was evaluated using various error metrics, with the best result achieved through the ANN method, which obtained a coefficient of determination of 98.89 % in the modelling of the energy demand. The RNN method has been identified as the most successful approach to modelling CO_2 emissions, achieving a determination coefficient of 96.80 %. After confirming the accuracy of the models, projections for Turkey's energy demand and CO_2 emissions over the next ten years have been made in three different scenarios: low, basic, and high. According to these estimates, energy demand is expected to range from 356 TWh to 378 TWh in 2025 and from 383 TWh to 425 TWh in 2035. Although energy demand has increased rapidly in recent years, the rate of growth is anticipated to decrease in the coming years. Similar estimates have been made for CO_2 emissions at three different levels. Emission levels are projected to be between 444 and 460 $MtCO_2$ in 2025 and between 451 and 472 $MtCO_2$ in 2035. While there is evidence that the rate of increase in CO_2 emissions has slowed over time, total emissions are still expected to rise, indicating that the net zero emission target is unlikely to be achieved under current conditions. Therefore, it is crucial to quickly implement innovative strategies that can meet both energy demand and support measures to reduce emissions.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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