A HYBRID PREDICTION APPROACH BASED ON ANN AND NAR NEURAL NETWORKS FOR ANNUAL ELECTRIC ENERGY DEMAND IN TURKEY

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Problems arise in economic and strategic planning when countries cannot foresee the energy demand for future periods. In the study, an estimation study has been conducted regarding the electric energy demand for the years 2021-2025 for Turkey. In this regard, artificial neural network (ANN) and regression analysis methods were applied. According to the results of the estimation study, the electricity consumption amounts will be 281.4 TWh, 294.3 TWh, 304.8 TWh, 307.2 TWh, and 316.9 TWh respectively for the years 2021-2025. Considering the results of the estimation, it is foreseen that there will be a continuous increase in the electric energy demand for future periods and it is significant to consider this increase when development policies for the country are planned in terms of economic and strategic planning. In future studies, it will be instructive to use the artificial neural networks and regression analysis methods that were applied in this study and conduct estimation studies for other parameters impacting the development level of the country.

Keywords: Electrical energy; Turkey; Artifical Neural Network (ANN); Autoregressive Neural Network (NAR); Regression analyses

1. Introduction

Turkey, due to its geographical location, has strategic importance between the Asian and European continents in terms of energy policies. Considering the changes in the country in the last ten years, while its population was 72.5 million in 2010, it increased by 15% compared to 2010 and reached 83.6 million people in 2020. While the Gross National Product was 777 billion dollars in 2010, it was 760 billion dollars in 2020 with a 2.2% decrease compared to 2010 [1]. Turkey is one of the countries with the highest increase in energy needs among OECD countries. With the increasing industrialization and technological developments and the increasing population, the need for electrical energy increases day by day. Since electricity consumption is continuous, production capacities, power plant maintenance periods, and energy reserves should be planned in a controlled manner in order to meet the needs in future periods and to prevent potential power cuts. Plans for future periods are made by

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conducting studies on electricity consumption prediction, electricity generation, electricity consumption, and price estimation [2].

Estimation methods are classified into two main groups as qualitative and quantitative estimation methods. Qualitative estimation methods are based on the expert's opinions and evaluations on the subject. Quantitative methods, on the other hand, are based on mathematical methods. Quantitative methods are also classified into two groups as cause-effect and time series analysis. In this study, an estimation of the future electric energy need of Turkey was made by using artificial neural networks (ANN), one of the quantitative estimation methods. The variables used in the literature were examined and the ANN model was established by determining the different variables that affect the electric energy demand. For the performance evaluation of the ANN model, other data mining regression methods (support vector machine-SVM, Gaussian process regression-GPR, and regression decision tree) were used, the results were compared with each other and the models working with performance were evaluated [3]

2. Literature Review

In the literature, many different estimation techniques are used for energy demand estimation. For example, by using estimation techniques such as time series [2], gray prediction [4], regression model [5], particle swarm optimization [6], genetic algorithm [7], fuzzy logic [8], artificial neural networks [9] etc., electric energy consumption amounts have been estimated.

In addition, in electric energy consumption studies conducted in Turkey, Ceylan et al used the genetic algorithm method [10], Yumurtaci and Asmaz the linear regression method [11], Akay and Atak the gray prediction method [12], Erdogdu cointegration analysis and ARIMA method [13], Toksarı ACO method [14], Demirel etc. ANFIS method [15], Kavaklioglu SVM method [16], Dilaver,and Hunt Structural time series [17] in their studies on electric energy consumption estimation. In the literature the artificial neural networks method (ANN) is a method frequently used in electric energy estimation studies. In electric energy consumption estimation studies in Turkey. The independent variables, data set, and data of the estimation period used by the authors in their studies are summarized in Table 1.

Table 1

A summary of the studies on forecasting electric energy consumption in Turkey

References	Methods	Variables	Forecasted energy type	Data	Forecasted Years
[24]	ANN technique	Transportation, agriculture, residence, industry sector	Net electricity energy consumption on sectoral basis	1970-2004	2003-2020
[2]	ANN technique	Population, gross	Basic energy	1975–	2004–2020

		generation, ınstalled capacity, net energy consumption, ımport, export	sources and net electricity energy consumption	2003	
[10]	Genetic algorithm approach	GDP, import/export, population	Energy and exergy production and consumption	1990–2000	2000–2020
[11]	Linear regression	Population, energy consumption increase rates per capita	Electricity demand	1980–2002	2003–2050
[12]	Grey prediction	-	Total and industrial electricity	1970-2004	2006-2015
[13]	Cointegration analysis and ARIMA	-	Electricity demand	1923-2004	2005-2014
[25]	ANN technique	Population, GNP, import, export	Electricity consumption	1975-2006	2007-2027
[14]	ACO	GDP, population, import, export	Electricity demand	1979-2006	2007-2025
[15]	ANFIS	-	Electricity demand	1970-2005	2006-2010
[16]	SVM	Population, GNP, import, export	Electricity consumption	1975-2006	2007-2027
[17]	Structural time series	household total final expenditure, real electricity prices	Electricity consumption	1960-2008	2008-2015
[26]	ANN technique	installed capacity, gross electricity generation, population and total subscribership	Electricity consumption	1990-2007	2008-2015
[27]	ANN technique	date, seasonal and economic status information	Electricity consumption	2005-2011	Short term forecast
[28]	ANN technique	population, import, export and building area	Electricity consumption	2002-2014	2016-2020
[29]	ANN, Time Series	energy consumption of previous days and temperature	Electricity consumption	2014-2016	Model is established
[30]	ANN technique	daily electricity demand	Electricity consumption	2012-2017	2018
[31]	ANN technique, SARIMA	-	Electricity consumption	2015-2018	Short term forecast
[32]	ANN technique	Hour, temperature, consumption	Electricity consumption	4 -18 April	Short term forecast
[33]	NARX ANN, LTSM	Time, Covid-19 precautions, and weather variables	Electricity consumption	Jan.-April 2019	Short term forecast

When similar country-based studies in the world were investigated, Pao made estimations for Taiwan [18], Bianco et al. for Italy [19], Mohamed and Bodger for New Zealand [20], Abdel-Aal and Al-Garni for Eastern Saudi [21], Zhou et al. for China [4], Bianco et al. for Romania [22], and Masaebi for Iran

[23] by using different methods in their studies on electricity consumption. The method used by the authors, independent variables, and the data of the countries on which the estimation was made are summarized in Table 2.

Table 2

Some studies on electrical energy forecasting for various countries.

References	Methods	Variables	Forecasted energy type	Countries
[18]	ANN technique, linear and non-linear statistical models	National income, GDP, consumer price index	Electricity consumption	Taiwan
[19]	Regression models	Population, GDP, GDP per capita	Electricity consumption	Italy
[20]	Multiple linear regression analysis	GDP, average price of electricity, population	Electricity consumption	New Zealand
[21]	ARIMA models and univariate Box–Jenkins time-series analysis	-	Monthly electric energy	Eastern Saudi
[4]	Trigonometric grey prediction	-	Electricity demand	China
[22]	Holt–Winters exponential smoothing method and trigonometric grey model with rolling mechanism	-	Electricity consumption	Romania
[23]	ANN technique	Growth rate, electricity selling price, import, export, GDP and population	Electricity consumption	Iran

3. Solution Structures

Artificial neural networks, regression analysis and nonlinear autoregressive (NAR) neural network methods were used as prediction methods in the study. In this section, information was given about the working principle and theoretical and technical structure of the structures mentioned. The performance Statistical error measures equations used in the modeling are explained.

3.1. Artificial neural networks

Artificial neural networks (ANN) consist of combining artificial nerve cells that are inspired by the working structure of biological nerve cells. ANN can learn and generalize, model nonlinear structures, is adaptable for different problems, and is error-tolerant [34]. Artificial neural networks do not require prior knowledge between input and output variables. It learns the relationship between the given input and output variables. This learning process is called supervised learning, and in the study, backpropagation algorithm, which is a supervised learning method, has been used. Learning with backpropagation algorithm in artificial neural networks consists of two stages. In forward propagation calculation, the input values are entered into the network with weight matrices and the output value is calculated. Then, with the aim of minimizing the error value between the output value created by the network and the actual value, the net weights are rearranged together with the backpropagation. This process continues until the network produces the desired output [35]. Artificial neural networks are used in prediction methods based on time series and in prediction methods based on cause-effect relationship. In ANN, input variables are independent variables, and output values are dependent variables. Nonlinear functional relationship for ANN is as in Equation 1 [3];

$$Y = f(x_1, x_1, \dots \dots x_n) \tag{1}$$

Here, $x_1, x_1, \dots \dots x_n$ refers to n pieces of independent variables, and Y refers to the dependent variable. For the predictions based on time series, ANN input variables represent the past period values of the data set, and the output represents the predicted value. Nonlinear relationship determined by ANN is represented as in Equation 2 [3];

$$Y_{t+1} = f(y_t, y_{t-1}, \dots \dots y_{t-n}) \tag{2}$$

3.2 Regression analyses

Regression analysis is a parametric method used to determine the correlation between two or more variables. It is one of the methods that are used to determine the correlation between two or more variables that have a cause-effect relationship and can make future predictions about that subject by using this correlation. The regression model uses estimation, classification and analytical data tools to determine the importance of many explanatory variables. There are two types of regression models that are simple regression with one independent variable and multiple regression analysis with more than one independent variable. Regression flow chart is as shown in Fig. 1.

Fig.1: This flow chart shows a common workflow for training regression models in the Regression Learner app [36].

In the study, regression algorithms in Matlab R2020a program were used and applied to our data set. These algorithms are Linear regression (Linear, interactions linear, robust linear); Regression trees (fine, medium); Support Vector Machines (linear, quadratic, cubic, fine gaussian, medium gaussian);

Ensemble Bagged Trees; Gaussian Process (squared exponential, matern 5/2 GPR, exponential quadratic, rational quadratic) algorithms.

Linear regression algorithm*;* is a way of modeling the relationship of a dependent variable, which is the basis of regression analysis, to one or more independent variables. The main purpose here is to estimate the value of the dependent variable based on the known or invariant values of the independent variables [37].

Regression trees*;* decision trees are in the form of a tree structure that can be built on both regression and classification models. While regression is used on numerical target data, classification is used on categorical data (eg yes / no). Decision trees consist of decision nodes and leaf nodes according to characteristics and goal [38].

Support Vector Machines*;* SVM algorithm draws the parallel furthest line to distinguish in each other the data which were formed as two groups [38].

Gaussian process regression (GPR) models*;* are nonparametric kernel-based probabilistic models. A machine learning algorithm involving the Gaussian process determines the measure of similarity between points using the kernel function to estimate the value of an unknown point from training data. Consider the training set {(xi,yi);i=1,2,...,n} where xi∈ℝd and yi ∈ℝ, drawn from an unknown distribution. A GPR model addresses the question of predicting the value of a response variable y new, given the new input vector x new, and the training data. A linear regression model is of the form as in Equation 3.

$$y=x^T\beta+\varepsilon \tag{3}$$

where ε∼N (0,σ2). The error variance σ2 and the coefficients β are estimated from the data. A GPR model explains the response by introducing latent variables, f(xi), , i=1,2,...,n, from a Gaussian process (GP), and explicit basis functions, h. The covariance function of the latent variables captures the smoothness of the response and basis functions project the inputs x into a p-dimensional feature space [38].

3.3 Nonlinear Autoregressive (NAR) Neural Networks

Nonlinear Autoregressive (NAR) Neural Network is defined as a self-repeating network with a feedback connection that includes several layers of the network. NAR model works based on linear autoregressive (AR) model for estimation in time series. The non-linear h (.) function calculates the output value of the next step depending on the p step previous values of the output signal [39];. Non-linear autoregressive (NAR) network is on Fig. 2, and the output value calculation equation is as in Equation 4;

$$y(t) = h(y(y-1),\ y(t-2), \dots, y(t-p)) + \epsilon(t) \tag{4}$$

Here, y (t) output value, h (.) indicates a nonlinear function. e(t) stands for the error of the approximation of the series y at time t. Non-linear autoregressive (NAR) network [40];

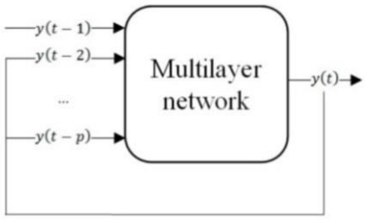


Fig.2: Non-linear autoregressive (NAR) network.

3.4. Statistical error measures

Performance measurement criteria Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and correlation coefficient (R2) were used in implementation. The correlation coefficient value indicates whether the regression equation is compatible with the data. It is the ratio of the explained change to the total change. It is an indicator of how much of the dependent variable results from the independent variable. It takes a value between 0-1, and the closer it is to 1, the more successful the program is. Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) values were preferred because they are used in many electricity consumption prediction studies and they are more practical for making comparisons. MSE, R2 and MAPE, RMSE, MAE calculations are given in Equations 5-9 [41];

$$\text{Mean Squared Error (MSE)} = \frac{\sum(e_t)^2}{N} \tag{5}$$

$$\text{Correlation Coefficient } (R^2) = 1 - \left(\frac{\sum_j |t_j - o_j|^2}{\sum_j |(o_j)|^2}\right) \tag{6}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \sum_{i=1}^{n} \left|\frac{e_i}{Y_i}\right| * 100 \tag{7}$$

$$\text{Root-mean-square error (RMSE)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f_i)^2} \tag{8}$$

$$\text{Mean Absolute error (MAE)} = \frac{1}{N}\sum_{i=1}^{n} |(y_i - f_i| \tag{9}$$

Here, e_i refers to the *i*. error (difference between the real value and the predicted value) value, y_i refers to the *i*. observation value, and *n* refers to the number of data. The higher the R^2 value and the lower the MAPE value, the better the predicted value. Studies with an MSE value of less than 10% in the literature are considered successful. Witt classified the prediction models with MAPE values below 10% as "high accuracy" and models between 10% and 20% as correct predictions [42]. Similarly, Lewis classified models with a MAPE value of less than 10% as "very good," models with a MAPE value between 10% and 20% as "good," models with a MAPE value between 20% and 50% as "acceptable," and models with a MAPE value of more than 50% as "false and erroneous" [43].

4. Results and discussion

The variables were determined by investigating the independent variables used in the study and the reason for selection. ANN models with different layers, functions and neuron numbers were made and performance evaluation was analyzed. In order to make a comparison with ANN results, regression analysis was performed, and performance values were obtained. The network with the best performance value among the models has been determined to be used in the prediction period. For the forecast period independent variable data, NAR modeling was performed, and future period independent variables were derived.

4.1. Selection of the predictor variables

When the electricity consumption estimation studies in the literature are examined, there are studies involving different combinations as socio-economic and independent variables in the selection of independent variables. It is seen that there is no joint study using historical data of population, export, import, consumer price index (CPI), and gross domestic product (GDP). Information on the variables used in the study are as shown in Table 3.

Table 3

Information on the variables used in the study.

Variable Name	Data Source	The Reason for Using the Variable
Population	[44]	As the population rate increases, electricity consumption is expected to change. Therefore, changes in these parameters are correlated with electricity consumption.
Import	[44]	The majority of primary sources in electricity generation are imported. Therefore, changes in these parameters are correlated with electricity consumption.
Export	[44]	It is an important variable in measuring a country's prosperity and growth. As the amount of exports increases, along with economic growth, electricity consumption in production areas, residences and many other places also increases. When there is a decrease, a decrease

		is expected likewise. Therefore, changes in this parameter are correlated with electricity consumption.
The Consumer Price Index (CPI)	[1]	It is defined as the change in the prices of a basket of products and services purchased by a particular household group. The CPI is a variable related to the purchasing power of the household. Factors such as the increase in living standards and the increase in purchasing power are highly correlated with electricity consumption. This indicator measures the change in CPI with the help of a reference index. In the data we have, the year 2015 is taken as the reference (2015 = 100).
Gross Domestic Product (Gdp)	[1]	As it is an indicator of growth, it also shows the consumption of electric energy in parallel.

In the study, using the data of these independent variables between the years 1990-2020, annual electricity consumption values[45] between 2021-2025 will be estimated. Information on the variables as given in Table 4 and Fig. 3 [1], [43], [44].

Table 4

Information on the variables used in the study

Year	Population (million)	Import (Bn $)	Export (Bn $)	CPI (2015=100)	GDP (million $)	Electrical Energy (TWh)
1990	55.4	13.0	22.3	26.1	150.7	46.8
1991	56.7	13.6	21.0	29.8	150.0	49.3
1992	57.8	14.7	22.9	29.5	158.5	54.0
1993	58.9	15.3	29.4	30.4	180.2	59.2
1994	60.1	18.1	23.3	46.3	130.7	61.4
1995	61.2	21.6	35.7	34.9	169.5	67.4
1996	62.3	23.2	43.6	34.4	181.5	74.2
1997	63.5	26.3	48.6	38.6	189.8	81.9
1998	64.6	27.0	45.9	33.2	276.0	87.7
1999	65.8	26.6	40.7	28.7	256.4	91.2
2000	66.9	27.8	54.5	21.4	274.3	98.3
2001	64.7	31.3	41.4	27.8	201.8	97.1
2002	65.6	36.1	51.6	16.4	240.2	102.9
2003	66.4	47.3	69.3	8.5	314.6	111.8
2004	67.2	63.2	97.5	4.3	408.9	121.1
2005	68.0	73.5	116.8	3.8	506.3	130.3
2006	68.9	85.5	139.6	5.0	557.1	143.1
2007	69.7	107.3	170.1	3.8	681.3	155.1
2008	70.6	132.0	202.0	5.5	770.4	161.9
2009	71.5	102.1	140.9	2.7	649.3	156.9
2010	72.6	113.9	185.5	3.9	777.0	172.1
2011	73.7	134.9	240.8	3.8	838.8	186.1
2012	74.7	152.5	236.5	3.9	880.6	194.9
2013	75.6	151.8	251.7	3.9	957.8	198.0
2014	76.7	157.6	242.2	4.4	938.9	207.4
2015	77.7	143.8	207.2	3.8	864.3	217.3
2016	78.7	142.5	198.6	3.8	869.7	231.2
2017	79.8	157.0	233.8	5.6	859.0	249.0
2018	80.8	167.9	223.0	10.0	778.4	258.2
2019	82.0	171.5	202.7	5.8	761.4	258.7
2020	83.2	169.5	219.5	5.4	527.3	270.9

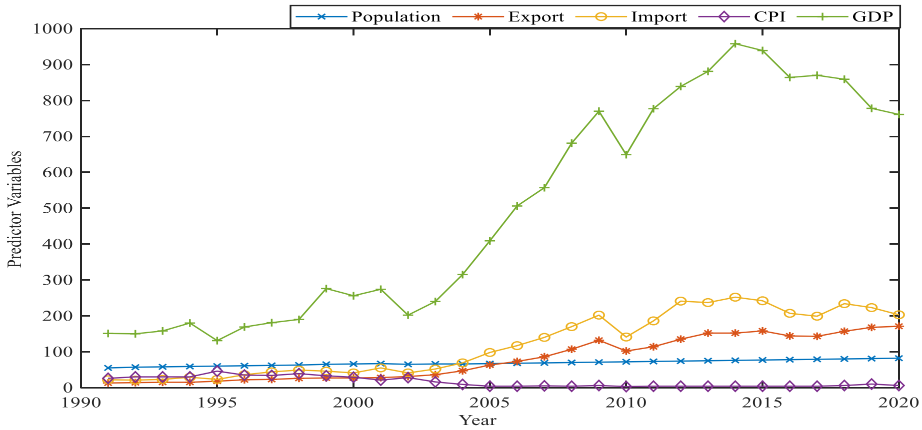


Fig.3: Information on the variables used in the study

4.2. NAR ANN algorithm used and future estimation of the predictor variables

In the study, the electricity consumption data for the forecast period 2021-2025 must be derived while population, export, import, CPI, and GDP values are present as independent variables. NAR neural network models were produced with hidden layers and neuron numbers which had different forecast periods, and the network model giving the lowest error was preferred. While determining the model, the data set training phase is randomly assigned as 80% training, 10% verification, and 10% test set. The number of delay steps shifts between 2 and 10 and the number of hidden layer neurons between 10 and 20, which results in the model giving the lowest error. ANN neural network diagram and model parameters are shown in Fig. 4 and Table 5 respectively;

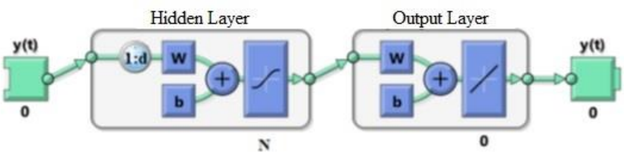


Fig.4: NAR neural network model

Table 5

Model parameters

Specifications	Values
Number of layers	5
Number of Time Delay (d)	2-10
Number of hidden layer neurons (N)	4
Weights and biases	Rastgele
Activation functions	Tan-Sigmoid, Doğrusal
Training algorithm	Levenberg-Marquardt
Epoch	1000

After evaluating the performance values of the NAR ANN model parameters experiment, the number of hidden layers was chosen as 2, hidden layer neurons as N: 5, the number of time delay as d: 4, the activation function as Tan-sigmoid, the training algorithm as Levenberg-Marquardt, and epoch as 1000. Table 6 shows the MSE, R-squared, and time series response values, which were obtained after individual trials of the NAR ANN model for each independent variable separately. R-squared value's proximity to 1.00 indicates that the model is successful. The values of training, validation and closeness of test R-squared to 1 for each independent variable can be seen more clearly in Fig. 5.

Table 6

NAR ANN model MSE, R- squared and time series response values.

Variables	Training	Validation	Test	R-squared
Population	0.999	0.974	0.999	0.996
Export	0.999	0.996	0.903	0.990
Import	0.967	0.836	0.999	0.971
CPI	0.965	0.970	0.756-0.856	0.8780.954
GDP	0.961	0.995	0.989	0.964

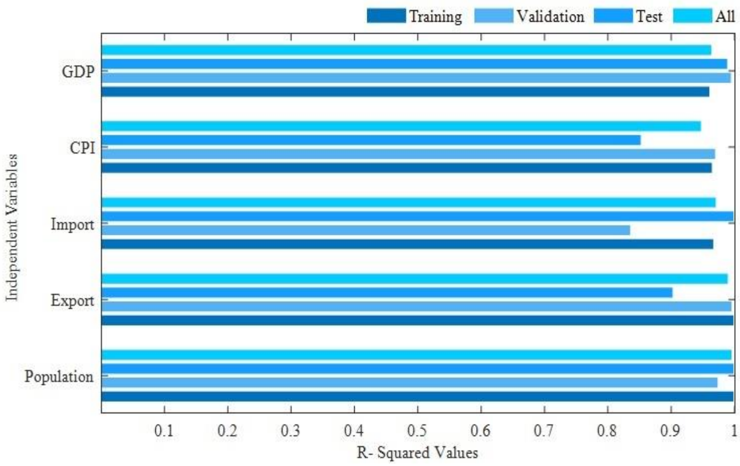


Fig.5: Training, validation, and test R-squared values for each data set

The 2021-2025 values of each independent variable were estimated by the trained NAR ANN model and values given in Table 7 were obtained. In order to view the obtained data together with the data of the previous years, the data produced by NAR have been compared with the available data set in Fig. 6.

Table 7

Independent variables estimated with the NAR function

Years	Population (million)	Export (Bn$)	Import (Bn$)	CPI (2015=100)	GDP (Bn$)
2021	84.61	157.9	276.6	7.37	635.6
2022	86.19	150.9	225.4	4.91	649.4
2023	87.56	154.9	201.7	3.51	814.2

2024	89.03	166.2	311.1	3.82	816.1
2025	90.09	170.3	207.6	3.54	869.9

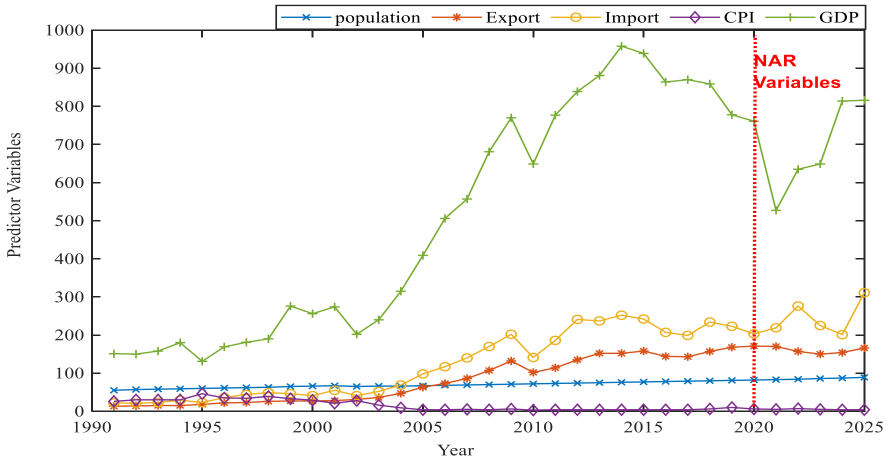


Fig. 6: Independent variables estimated with the NAR function

4.3. Artifical neural network architecture

The data for the years 1990-2020 were obtained from official sources and entered in Matlab ".m" files. 70% of the data was used as training, 15% as verification, and 15% as test data set. Feed forward back propagation neural network architecture is given in Fig. 7 and all variables have been transformed into the interval [0-1] by normalization; the normalization is defined as in Equation 10;

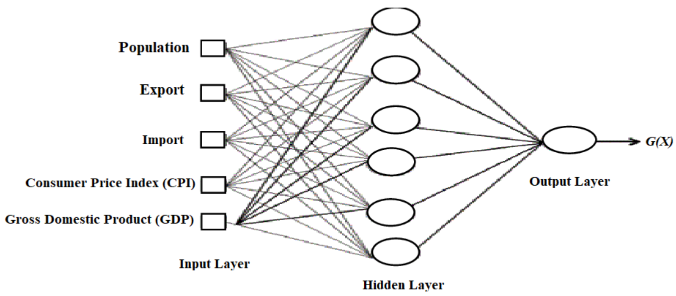


Fig. 7: Neural network architecture

$$x_n = (x_0 - x_{min})/(x_{max} - x_{min}) \tag{10}$$

Levenberg-Marquardt training algorithm was used in Matlab Training stage. The default parameters of Matlab R2020a were used for the training algorithm. For this, the maximum number of iterations was determined as 1000, Minimum Performance Gradient as 1e-7, Initial mu value as 0.001, mu increase factor as 10, mu decrease factor as 0.1, and maximum mu as 1e10. Validation data, unlike training data, is given to the network while training, and the overfitting status of the network is checked. The decision that the training of the network is sufficient and to stop the training is made during this step. Test data is given to the network that has been trained and verified. At this stage, the actual output value of the test data is compared with the estimated output value calculated on the network. If the error value is at the desired level, the next step is taken, otherwise the process is repeated. The loop is closed, and the network is saved. The network is brought into a state where new input values can be given and the output value can be predicted. Different neural architectures have been tried with the aim of finding the most successful network model. Network type is Feed-Forward Backprop and dividerand is used as data partition type. The network models, functions, MAPE and R-squared values that have been tested are given in Table 8 below.

Table 8

Comparative ANN learning algorithm and network structure results

Model No.	Activation Function		Training Function	Validation Function	Number of Neurons	MAPE			R^2
	First Layer	Second Layer				Training	Validation	Test	
1	Tansig	N	Trainlm	LearnGDM	1-N	0.028	0.02	0.168	0.996
2	Tansig	N	Trainlm	LearnGDM	1-N	0.04	0.031	0.179	0.996
3	Tansig	N	Traingdx	LearnGDM	1-N	0.038	0.029	0.178	0.994
4	Tansig	N	Traingdx	LearnGDM	1-N	0.031	0.027	0.166	0.996
5	Logsig	N	Trainlm	LearnGDM	1-N	0.47	0.034	0.179	0.872
6	Logsig	N	Trainlm	LearnGD	1-N	0.47	0.024	0.172	0.88
7	Logsig	N	Traingdx	LearnGD	1-N	0.472	0.031	0.165	0.89
8	Logsig	N	Traingdx	LearnGDM	1-N	0.472	0.034	0.176	0.88
9	Tansig	Tansig	Trainlm	LearnGDM	2-1	0.02	0.017	0.173	0.997
10	Tansig	Tansig	Trainlm	LearnGDM	3-1	0.019	0.011	0.153	0.994
11	Tansig	Tansig	Trainlm	LearnGDM	4-1	0.013	0.010	0.154	0.999
12	Tansig	Tansig	Trainlm	LearnGDM	5-1	0.035	0.025	0.205	0.995
13	Tansig	Tansig	Trainlm	LearnGDM	6-1	0.057	0.042	0.163	0.994
14	Tansig	Tansig	Trainlm	LearnGDM	7-1	0.012	0.003	0.151	0.998
15	Tansig	Tansig	Trainlm	LearnGDM	10-1	0.033	0.003	0.156	0.986
16	Tansig	Tansig	Trainlm	LearnGDM	12-1	0.027	0.008	0.155	0.998
17	Tansig	Tansig	Trainlm	LearnGDM	15-1	0.11	0.124	0.159	0.945
18	Tansig	Tansig	Trainlm	LearnGDM	18-1	0.06	0.0003	0.152	0.990
19	Tansig	Tansig	Trainlm	LearnGDM	20-1	0.024	0.015	0.162	0.998
20	Tansig	Logsig	Trainlm	LearnGDM	2-1	0.47	0.028	0.154	0.90
21	Tansig	Logsig	Trainlm	LearnGDM	3-1	0.47	0.011	0.152	0.89
22	Tansig	Logsig	Trainlm	LearnGDM	5-1	0.462	0.023	0.151	0.889
23	Tansig	Logsig	Trainlm	LearnGDM	4-1	0.469	0.031	0.186	0.888
24	Tansig	Logsig	Trainlm	LearnGDM	7-1	0.463	0.008	0.156	0.896
25	Tansig	Logsig	Trainlm	LearnGDM	6-1	0.461	0.009	0.157	0.90
26	Tansig	Logsig	Trainlm	LearnGDM	10-1	0.471	0.026	0.160	0.88
27	Tansig	Logsig	Trainlm	LearnGDM	12-1	0.463	0.009	0.153	0.90
28	Tansig	Logsig	Trainlm	LearnGDM	14-1	0.467	0.025	0.179	0.895
29	Tansig	Logsig	Trainlm	LearnGDM	16-1	0.459	0.004	0.155	0.897
30	Tansig	Logsig	Trainlm	LearnGDM	18-1	0.466	0.017	0.159	0.878
31	Tansig	Logsig	Trainlm	LearnGDM	20-1	0.484	0.065	0.312	0.92
32	Logsig	Tansig	Trainlm	LearnGDM	2-1	0.095	0.061	0.284	0.979
33	Logsig	Tansig	Trainlm	LearnGDM	3-1	0.015	0.021	0.188	0.997
34	Logsig	Tansig	Trainlm	LearnGDM	5-1	0.043	0.062	0.202	0.995
35	Logsig	Tansig	Trainlm	LearnGDM	4-1	0.020	0.007	0.154	0.998

36	Logsig	Tansig	Trainlm	LearnGDM	7-1	0.040	0.052	0.185	0.995
37	**Logsig**	**Tansig**	**Trainlm**	**LearnGDM**	**6-1**	**0.011**	**0.02**	**0.160**	**0.999**
38	Logsig	Tansig	Trainlm	LearnGDM	10-1	0.078	0.027	0.194	0.986
39	Logsig	Tansig	Trainlm	LearnGDM	12-1	0.018	0.034	0.232	0.995
40	Logsig	Tansig	Trainlm	LearnGDM	14-1	0.028	0.009	0.156	0.996
41	Logsig	Tansig	Trainlm	LearnGDM	16-1	0.018	0.011	0.155	0.998
42	Logsig	Tansig	Trainlm	LearnGDM	18-1	0.034	0.021	0.183	0.993
43	Logsig	Tansig	Trainlm	LearnGDM	20-1	0.039	0.007	0.164	0.986

In the trials, different activation combinations were trained with different numbers of neurons, and MAPE, MSE, and R^2 values were examined. The activation combinations and adapting function was changed for one layer first, then for two layers, with the aim of reaching the network with the best performance value. As a result of the trials, it was seen that network number 37 gave the best prediction result when the results of $MAPE_{training}$, $MAPE_{validation}$, and $MAPE_{test}$ were evaluated together. During the evaluation, the model with the lowest $MAPE_{test}$ value that provides $MAPE_{training} < MAPE_{validation} < MAPE_{test}$, where these values are close to each other was selected. Network architecture of the network that provides the best performance, mean square error graph, and regression graph are given in Figs. 8, 9 and 10 respectively.

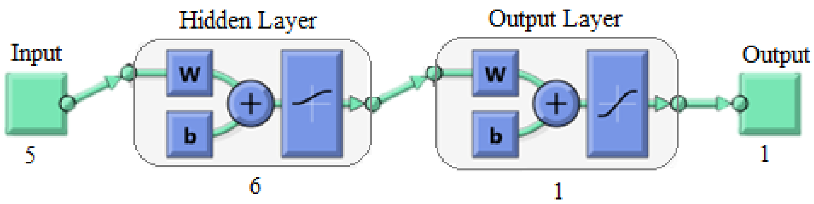
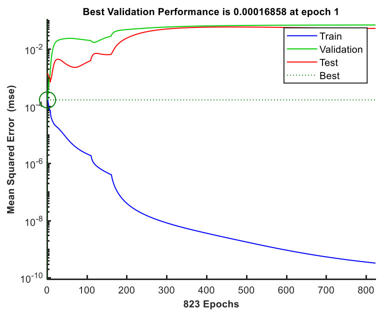


Fig. 8: Architecture of the network no. 37.



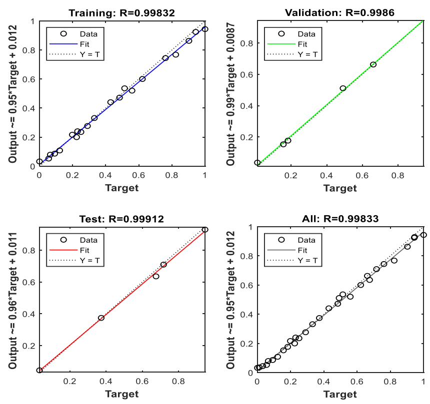


Fig. 9: Performance graph of the network no. 37. Fig. 10: Regression graph of the network no. 37.

4.4. Regression analysis

In this study, performance analysis of regression models for electricity consumption estimation was performed using the independent variables data set used in the ANN model. Analysis models and performance values which are RMSE, R-squared, MSE, MAE, Training time are as shown in Table 9 and comparison of RMSE values of models as shown in Fig. 11. Cross validation (K-fold) was chosen as 10 in the regression analysis.

Table 9

Regression model and performance values

Model No	Model Type	RMSE	R^2	MSE	MAE	Training Time (sec)
1	Linear Regression -Linear	0.0323	0.99	0.0010446	0.0250	5.14
2	Linear Regression Interactions	0.0281	0.99	0.00079	0.0194	4.63
3	Linear Regression- Robust Linear	0.0368	0.99	0.00135	0.0277	8.00
4	Stepwise Linear Regression	0.0209	1.00	0.0004	0.0147	9.42
5	Fine tree	0.0997	0.90	0.0099	0.0881	3.66
6	Medium tree	0.163	0.73	0.0265	0.1360	3.26
7	Lİnear SVM	0.0338	0.99	0.0011	0.0271	7.50
8	Quadratic SVM	0.0324	0.99	0.001	0.028	7.35
9	SVM Cubic SVM	0.0547	0.97	0.0029	0.040	7.13
10	Fine Gaussian SVM	0.166	0.72	0.0273	01092	6.87
11	Medium Gaussian SVM	0.0533	0.97	0.0028	0.0397	6.61
12	Ensemble Bagged Trees	0.1696	0.71	0.0287	0.1192	8.28
13	Squared Exponential GPR	0.0173	1.00	0.0003	0.0136	7.98
14	**Matern 5/2 GPR**	**0.0172**	**1.00**	**0.0002**	**0.0132**	**7.82**
15	Exponential Quadratic GPR	0.0320	0.99	0.001	0.0204	7.70
16	Rational l Quadratic GPR	0.0173	1.00	0.0003	0.0139	7.58

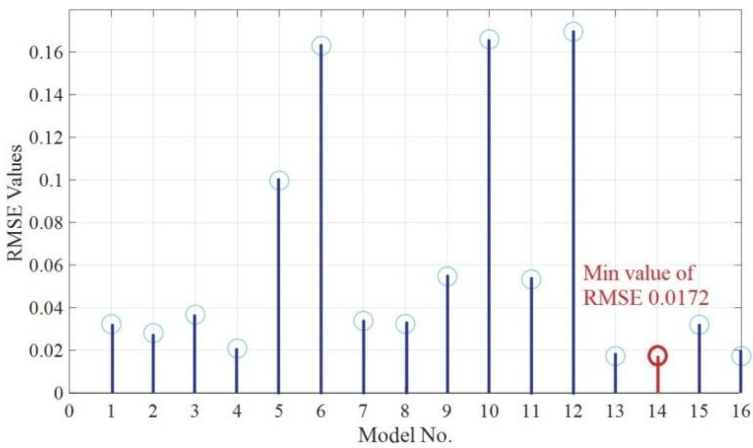


Fig. 11: Comparison of RMSE values of models

As a result of the analysis, the model No 14 with the lowest RMSE value was selected as the most successful model, and the prediction was made according to this model. Fig. 12 shows the true, predicted value comparison of Matern 5/2 GPR model no 14.

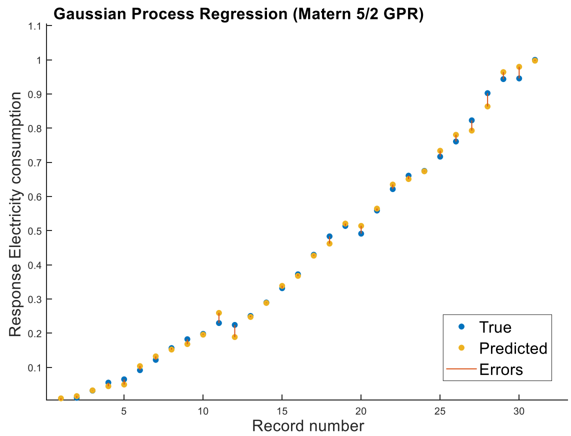


Fig.12: Predicted and true value comparison of Matern 5/2 GPR (model no 14)

4.5. Results

The ANN model no 37 and the regression model no.14 with the best performance value among the ANN and regression models that have been trained with the data set, have been made to perform electricity consumption estimation for the years 2021-2025 with the independent variables derived from NAR. The network structure for hybrid model, consumption data for both models were obtained and electricity consumption prediction values for the years between 2021 and 2025 are shown in Figure 13, Table 10 and Fig. 14 respectively.

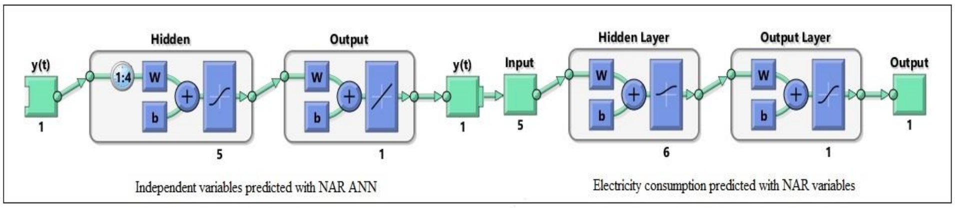


Fig.13: The network structure for hybrid model

Table 10

Electricity consumption prediction values for the years between 2021 and 2025

Year	Artifical Neural Network model no. 37	Gaussian ProcessMatern 5/2 model no.14
2021	281.4	294
2022	294.3	296
2023	304.8	299
2024	307.2	319
2025	316.9	294

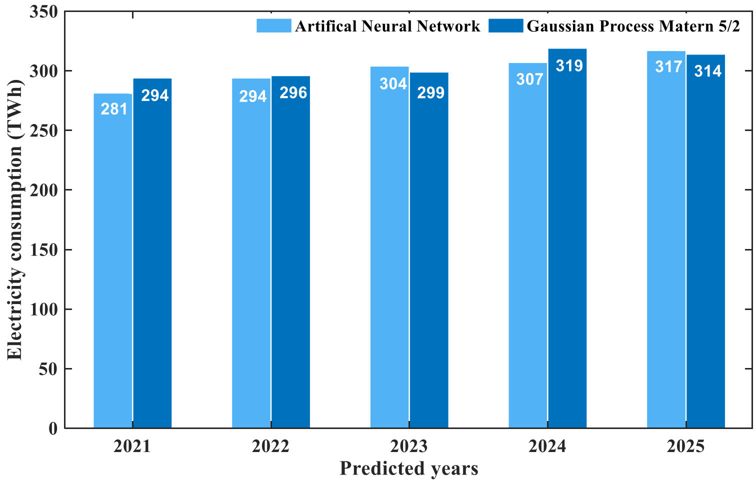


Fig. 14: Electricity consumption prediction values for the years between 2021 and 2025

When the Artifical Neural Network model no. 37 and Gaussian Process Matern 5/2 model no.14 predicted values are examined, it is seen that there is a difference of 4.42% for 2021, 0.675% for 2022, 1.67% for 2023, 3.76% for 2024, and 0.955% for 2025 between the predicted values of the models. Comparison of MSE and Training time performance of the models is as shown in Table 11.

Table 11

Comparison of ANN model and regression model parameters

Model	MSE	Training Time (sec)
Artifical Neural Network model no. 37	0.000168	1.00
Gaussian ProcessMatern 5/2 model no.14	0.000264	7.82

As it can be seen from the table, it is predicted that the predicted values of the ANN model will give results closer to the true values, as the MSE and training time performance of the model are better. The fact that there is not much difference with the regression model results indicates that there is no high incompatibility between the models.

5. Conclusion

Due to the geographical location, Turkey is a country in a strategic location and different energy policies are being implemented. Making reliable estimations for the future for electric energy consumption is very important for the correct implementation of energy policies. In the study, the models and independent variables in the literature study were examined and the ANN model was developed by considering these parameters. With the NARX algorithm, 2021-2025 future independent variables were derived and a hybrid model with ANN was created. In order to evaluate the ANN performance values, many regression models were developed, and the ANN results were compared with the model providing maximum performance. It was determined that with the proposed ANN model, which was suggested as a result of the analyses and comparisons performed, high-accuracy estimates were made. The results of the study are important for all institutions related to energy production, especially the Ministry of Energy and Natural Resources of Turkey. In future studies, different parameters that affect electricity consumption demand will be investigated and long-term studies will be conducted.

REFERENCES

[1]. *"World Bank,"* The world bank open data. [Online]. Available: https://data.worldbank.org/country/turkey?locale=tr. [Accessed: 12-Jan-2021].

[2]. *A. Sozen and E. Arcaklioglu,* "Prospects for future projections of the basic energy sources in Turkey," Energy Sources B Econ Plann Policy, **vol. 2**, pp. 183–201, 2007.

[3]. *C. Hamzacebi,* Artificial Neural Networks: Predictive Use of Matlab and Neurosolution. Bursa: Ekin Publishing, 2011.

[4]. *P. Zhou, B. Ang, and K. Poh*, "A trigonometric grey prediction approach to forecasting electricity demand," Energy, **vol. 31**,2006, pp. 2839–47.

[5]. *M. Bessec and J. Fouquau,* "The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach," Energy Econ., **vol. 30**, no. 5, 2008, pp. 2705–2721.

[6]. *J. Wang, S. Zhu, W. Zhang, and H. Lu*, "Combined modeling for electric load forecasting with adaptive particle swarm optimization," Energy, **vol. 35**, no. 4, 2010, pp. 1671–1678.

[7]. *Y. S. Lee and L. I. Tong,* "Forecasting energy consumption using a grey model improved by incorporating genetic programming," Energy Convers. Manag., **vol. 52**, no. 1, 2011, pp. 147–152.

[8]. *S. Kucukali and K. Baris*, "Turkey's short-term gross annual electricity demand forecast by fuzzy logic approach," Energy Policy, **vol. 38**, no. 5, 2010, pp. 2438–2445.

[9]. *Z. Geem and W. Roper*, "Energy demand estimation of South Korea using artificial neural network," Energy Policy, vol. 37, pp. 4049–54, 2009.

[10]. *H. Ceylan, H. K. Ozturk, A. Hepbasli, and Z. Utlu*, "Estimating energy and exergy production and consumption values using three different genetic algorithm approaches, part 2: application and scenarios," Energy Sources, **vol. 27**, 2005, pp. 629–39.

[11]. *Z. Yumurtaci and E. Asmaz,* "Electric energy demand of Turkey for the year 2050," Energy Sources, **vol. 26**, 2004, pp. 1157–64.

[12]. *D. Akay and M. Atak,* "Grey prediction with rolling mechanism for electricity demand forecasting of Turkey," Energy, **vol. 32**, no. 9, 2007, pp. 1670–1675.

[13]. *E. Erdogdu,* "Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey," Energy Policy, **vol.** 35, no. 2, 2007, pp. 1129–1146.

[14]. *M. D. Toksari,* "Estimating the net electricity energy generation and demand using the ant colony optimization approach: Case of Turkey," Energy Policy, **vol**. **37**, no. 3, 2009, pp. 1181–1187.

[15]. *Ö. Demirel, A. Kakilli, and M. Tektas*, "Electrical Energy Load Estimation with Anfis and Arma Models" J. Fac. Eng. Archit. Gazi Univ., **vol. 25**, no. 3, 2010, pp. 601–610.

[16]. *K. Kavaklıoğlu,* "Modeling and prediction of Turkey's electricity consumption using Support Vector Regression," Appl. Energy, **vol. 88**, no. 1, 2011, pp. 368–375.

[17]. *Z. Dilaver and C. H. Lester,* "Industrial electricity demand for Turkey: A structural time series analysis," Energy Econ., **vol. 33**, no. 3, 2011, pp. 426–436.

[18]. *H. T. Pao,* "Comparing linear and nonlinear forecasts for Taiwan's electricity consumption," Energy, **vol. 31,** no. 12, 2006, pp. 2129–2141.

[19]. *B. Bianco, O. Manca, and S. Nardini,* "Electricity consumption forecasting in Italy using linear regression models," Energy, **vol. 34**, 2009, pp. 1413–21.

[20]. *Z. Mohamed and P. Bodger,* "Forecasting electricity consumption in New Zealand using economic and demographic variables," Energy, **vol. 30**, 2005, pp. 19833–43.

[21]. *R. Abdel-Aal and A. Al-Garni*, "Forecasting monthly electric energy consumption in Eastern Saudi Arabia using univariate time-series analysis," Energy, **vol. 22**, 1997, pp. 1059–69.

[22]. *V. Bianco, O. Manca, S. Nardini, and A. Minae*, "Analysis and forecasting of nonresidential electricity consumption in Romania," Appl Energy, **vol. 87,** 2010, pp. 3584–3590.

[23]. *Pageh Masaebi*, "Iran Electric Energy Consumption Forcasting Using Artifical Neural Network," Mater Thesis, Karadeniz Technical University The Graduate School of Natural and Applied Sciences Department of Industry Engineering, Turkey, 2016.

[24]. *C. Hamzacebi and F. Kutay,* "Electric Consumption Forecasting Of Turkey Using Artificial Neural Networks Up To Year 2010" J. Fac. Eng. Archit. Gazi Univ., **vol. 19,** no. 3, 2004, pp. 227–233.

[25]. *K. Kavaklıoglu, H. Ceylan, H. K. Ozturk, and O. E. Canyurt*, "Modeling and prediction of Turkey's electricity consumption using Artificial Neural Networks," Energy Convers. Manag., **vol. 50**, no. 11, 2009, pp. 2719–2727.

[26]. *M. Bilgili, A. Sahin, and E. Simsek,* "Electric energy demands of Turkey in residential and industrial sectors" ," Renew. Sustain. Energy Rev., **vol. 16**, no. 1, 2012, pp. 404–414.

[27]. *B. Basoglu and M. Bulut,* "Development of a hybrid system based on neural networks and expert systems for shortterm electricity demand forecasting," Mühendis. Mimar. Fakültesi Derg., **vol. 32,** no. 2, 2017, pp. 575–583.

[28]. *Y. Kocadayi, O. Erkaymaz, and R. Uzun*, "Estimation Of Tr81 Area Yearly Electric Energy Consumption By Artificial Neural Networks," Bilge Int. J. Sci. Technol. Res., **vol. 1,** 2017, pp. 59–64.

[29]. *S. Ozden and A. Ozturk,* "Yapay sinir ağları ve zaman serileri yöntemi ile bir endüstri alanının (ivedik OSB) elektrik enerjisi ihtiyaç tahmini," Bilişim Teknol. Derg., **vol. 11**, no. 3, 2018, pp. 255–261.

[30]. *E. Haliloglu and B. Tutu,* "Forecasting Daily Electricity Demand For Turkey," Turk. J. Energy Policy, **vol. 3**, no. 7, 2018, pp. 40–49.

[31]. *C. Hamzacebi, H. A. Es, and R. Cakmak*, "Forecasting of Turkey's monthly electricity demand by seasonal artificial neural network," Neural Comput Applic, **vol. 31**, 2019, pp. 2217–2231.

[32]. *S. Tosun, A. Ozturk, and Taspinar, F.,* "Short Term Load Forecasting for Turkey Energy Distribution System with Artificial Neural Networks," Teh. Vjesn.-Tech. Gaz., **vol. 26**, no. 6, 2019, pp. 1545–1553.

[33]. *H. Ozbay and Dalcalı,* "Effects of COVID-19 on electric energy consumption in Turkey and ANN-based short-term forecasting," Turk J Elec Eng Comp Sci, **vol. 29**, 2021, pp. 78–97.

[34]. *Z. Sun, L. Qingdang, and L. Wang,* "Deep Learning Based Visual Object Tracker With Template Update," Univ. Politeh. Buchar. Sci. Bull. Ser. C-Electr. Eng. Comput. Sci., **vol. 82**, no. 2, 2020, pp. 65–76.

[35]. *C. Nutescu and M. Mocanu*, "Test Data Generation Usıng Genetic Algorithms And Information Content," Univ. Politeh. Buchar. Sci. Bull. Ser. C-Electr. Eng. Comput. Sci., **vol. 82**, no. 2, 2020, pp. 33–44.

[36]. *C. Karaca and H. Karacan*, "Investigation Of Factors Affecting Demand For Electricity Consumption With Multiple Regression Method" SUJEST, **vol. 4**, no. 3, 2016, pp. 182–195.

[37]. *M. A. Naouni, B. Lejdel, and M. Ayad,* “Integrating Iot Devices And Deep Learning For Renewable Energy In Big Data System,” Univ. Politeh. Buchar. Sci. Bull. Ser. C-Electr. Eng. Comput. Sci., **vol. 82**, no. 3, 2020 pp. 251–266.
[38]. *C. E. Rasmussen and C. K. I. Williams*, Gaussian Processes for Machine Learning. Cambridge Massachusetts: MIT Press, 2006.
[39]. *E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard*, “Wind Speed Prediction Using a Univariate ARIMA Model and a Multivariate NARX Model,” Energies, **vol. 9**, no. 2, 2016, pp. 1–15.
[40]. *D. Koschwitz, J. Frisch, and C. Van Treeck*, “Data-driven heating and cooling load predictions for non-residential buildings based on support vector machine regression and NARX Recurrent Neural Network: A comparative study on district scale,” Energy, **vol. 165**, 2018, pp. 134–142.
[41]. *G. Zhang, B. E. Patuwo, and M. Y. Hu*, “Forecasting with Artificial Neural Networks:The State of the Art,” Int. J. Forecast., **vol. 14**, no. 1, 1998, pp. 35–62.
[42]. *M. A. Sonmez and M. Bagriyanik,* “Generating Manageable Electricity Demand Capacity for Residential Demand Response Studies by Activity-based Load Models,” Adv. Electr. Comput. Eng., **vol. 21**, no. 1, 2021, pp. 99–108.
[43]. *D. Cinar, G. Kayakutlu, and T. Daim,* “Development of future energy scenarios with intelligent algorithms: Case of hydro in Turkey,” Energy, **vol. 35**, no. 4, 2010, pp. 1724–1729.
[44]. *“TUIK,”* Turkısh Statistical Institute. [Online]. Available: http://www.tuik.gov.tr./. [Accessed: 05-Jan-2021].
[45]. *“MENR,”* Turkish Ministry of Energy and Natural Sources. [Online]. Available: http://www.enerji.gov.tr/istatistik.asp./. [Accessed: 25-Oct-2020].