THE OPTIMIZED ARTIFICIAL NEURAL NETWORK BASED ESTIMATION OF ELECTRICITY GENERATION OF TURKEY

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ABSTRACT

Energy production is the most important indicator of the economic development of a country. Increasing investment in renewable energy sources increases the sustainability of clean energy while reducing dependence on energy resources, which is inevitable to be consumed. Turkey has a wide variety of renewable energy sources such as hydro, biogas, wind, geothermal and solar, shows that the future energy needs can be met from environmentally friendly sources of energy. The aim of this study is to forecast the future status of Turkey's renewable and thermal energy generation potential. The second objective is to apply the optimal artificial neural network (ANN) model for this estimation with feed forward back propagation (BP) and cascade forward back propagation (BP) algorithms.

1. INTRODUCTION

The sustainability of energy and the diversity of energy resources are important criteria for determining the economic policies of countries [1-3]. At this point, the estimation of electricity energy generation plays an important role in the adjustment of future energy organizations. Therefore, the establishment of a model with good accuracy for estimation will greatly affect future energy investments. There are many methods such as regression, time series, artificial intelligence based which are used for estimation [4]. Time series methods such as autoregressive integrated moving average (ARIMA), autoregressive moving average exogenous (ARMAX), and Kalman filtering are not suitable for nonlinear situations [5]. It is the most common method used in the literature is ANN models with good results for nonlinear structure systems between multiple input values and the output variable that these values affect [6,7]. In addition, there must be a balance between fossil-based energy production and renewable energy generation. Investments in renewable energy resources such as hydroelectricity and wind, which are clean and endless sources of energy, and in fossil resources that are the finite energy source, should be evaluated taking into account the advantages of each.

Turkey is in a position rapidly growing country in terms of population and economy. As a result, demand for electricity is rapidly increasing [8]. According to the data obtained from Turkish Electricity Transmission Company, the annual changes of electric energy generation and of the population data are shown in Table 1. By the end of July 2017, the generated electricity became by using the different sources which were of 34% from natural gas, of 31% from coal, of 24% from hydraulic power, of 6% from wind, of 2% from geothermal energy and of 3% from other sources, to generate the total of Turkey’s electricity. Electricity consumption increased by 4.7% to 167.1 billion kWh and electricity generation increased by 6.7% to 167.3 billion kWh by the end of July 2017, compared to the end of July of the previous year [9].

There are a number of case studies that have been done to Turkey's electricity demand, electricity energy consumption and generation forecasting. One of them, Toksari applied the ant colony algorithm for estimating the demand and generation of Turkey's electricity energy [8]. In the model, variables such as population, gross domestic product (GDP), import and export variables are input variables. In another study, that ant colony algorithm is used, a model was obtained for the prediction of Turkey's energy demand [10]. Turkey's future energy demand was estimated using a genetic algorithm [11]. The results of the other models, which are derived from the genetic algorithm for energy demand and consumption.

Table 1. Annual electricity generation of Turkey for years 1990-2017

		Generation (GWh)		
Years	Population (10^6)	Thermal	Hydro	Geothermal +Wind +Solar
1990	53,92	34315	23147,6	80,1
1995	58,49	50621	35540,9	86,0
2000	63,24	93394	30878,5	108,9
2005	67,90	122242	39560,5	153,4
2010	72,33	155828	51795,5	3584,6
2015	78,27	179367	67145,8	15271,0
2016	79.51	185798,1	67231,0	21378,7

estimation, are presented in the studies of [12-13]. In the study done in [14], thermal and hydro energy production was estimated in the model using the genetic algorithm with time series approach. The consumption of electric energy up to 2010 was estimated by using ANN model [15]. The other was used two different ANN models, which were different variables in the input layer to forecast the future net energy consumption of Turkey [16]. Similarly, energy consumption estimation using the ANN model in [17-18]. In [19], ANN and regression techniques have been used for estimating the energy consumption created by considering GDP, population, import and export magnitudes, and the ANN model has been found to be more efficient in estimation. For Turkey's hydroelectric energy production forecasting the ANN-artificial bee colony hybrid model result, and classical ANN with back propagation (BP) algorithm model result were compared [20].
The main contribution of this study is to estimate the future renewable and thermal source energy production using high accuracy using the ANN model. Therefore, different learning algorithms (feed forward BP and cascade forward BP) have been tried with different training functions to obtain the best model.

2. PROPOSED ANN STRUCTURE

ANN models are among the best-known methods for solving nonlinear problems such as estimation, classification etc. with more than one variable. As shown in Fig. 1 an ANN basically consists of input, output, and hidden layers. Each layer has neurons in different numbers that are the processing elements of the network. The connection between neurons in different layers is realized by weights. The initial weight is updated by comparing the actual output value with the desired output during the training period. Thus, errors are reduced most. After the weights have been summed, the system switches to the activation function and this activated value are the output value of the network.

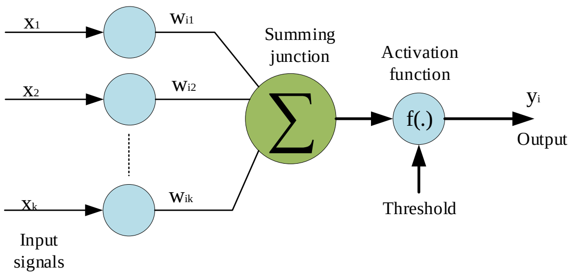

Fig. 1. Basic ANN structure

Another important function of the network is to determine the response of the neural network to each of the variables in the input layer. In another word, it is the evaluation of how the variables are propagated from the input to the output layer in the associated network.
In this study, Cascade-forward BP and feed-forward BP learning algorithm are used to estimate the future thermal and renewable energy production of Turkey. Because the BP algorithm gives better results than the other algorithms in determining the optimal weights to reduce the error between actual and desired output values. The cascade-forward BP model and the feed-forward BP model are the same network structure, but it differs from the input layer to the weight relationship to all other layers [18]. Also, in the training of neural

network, two different training functions which were Levenberg-Marquardt and Gradient Descent, were applied, and the effect of these functions on network accuracy was examined.

2.1. Case Application of Energy Generation Forecasting

In this current paper, as shown in Fig. 2, gross electricity energy demand (GEED), population, gross domestic product (GDP) and installed capacity are determined as input variables, thermal energy and renewable energy generation as output parameters.

When the population and GDP data are obtained from the World Bank, the installed capacity, GEED, and energy generation data are taken from Turkish Electricity Transmission Company. The dataset was created with 40 data between 1975 and 2015 belonging to these parameters for the training of the model. The distribution interval of data is irregular, meaning that the difference between the values of the data is so great that ANN's training process becomes difficult. For this reason, the input data has been normalized to facilitate the training period. To degrade a data in the range between 0 and 1, Eq. (1) is used.

$$x_{nor} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Where, x_{nor} is the normalized value, x_i is the input value, $x_{\min}$ is the minimum value of the input data and the $x_{\max}$ is the maximum value of the input value.

2.2. Performance Analysis of the Model

The defined network is modeled using artificial neural network toolbox of the MATLAB environment. The model is trained using two different learning algorithms and training function. The hidden layer has 10 neurons and then, the network trained 10 times for each algorithm. Table 2 presents the results.

The regression results of the validation process of the network trained according to Table 2 are given. The fact that the results are close to 100 % indicates that the accuracy of estimating the output parameters of ANN is good. As can be seen from the results, it is seen that the learning algorithms and training functions have an effect on the estimation performance. In this study, the best regression result is obtained by

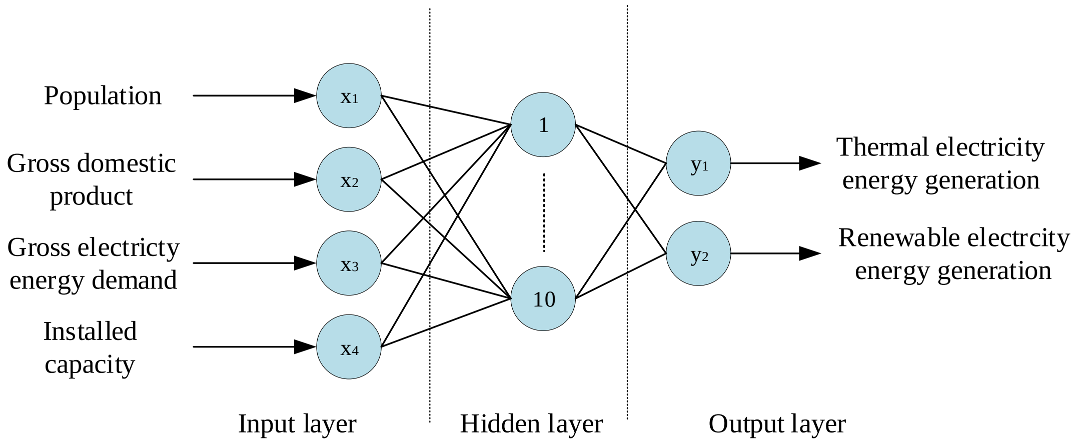

Fig. 2. ANN forecasting model

Table 2. Regression results of the different ANN models

Learning Algorithm	Training function	R Percentage Values for Different Training (%)										
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	Mean Value
Feed-forward BP	**Levenberg Marq.**	98.86	96.34	99.45	98.17	95.94	91.19	98.08	94.61	96.94	97.55	96.71
	Gradient Descent	92.00	83.33	89.90	72.85	99.00	97.70	95.14	98.88	98.73	93.62	92.12
Cascade-forward BP	**Levenberg Marq.**	93.96	99.26	99.42	99.93	99.80	98.63	99.63	93.73	99.68	99.48	**98.35**
	Gradient Descent	68.31	98.33	96.63	97.79	93.84	96.12	99.02	95.79	98.94	95.10	93.99

using cascade-forward BP and Levenberg-Marquardt in combination as shown in Fig. 3. The table 2 also indicates that Cascade-forward ANN model is a useful method to predict the estimation of future electricity generation with nearly 99% of accuracy result. The mean square error value for the best validation performance that is less than 0.001 is also given in Fig. 4.

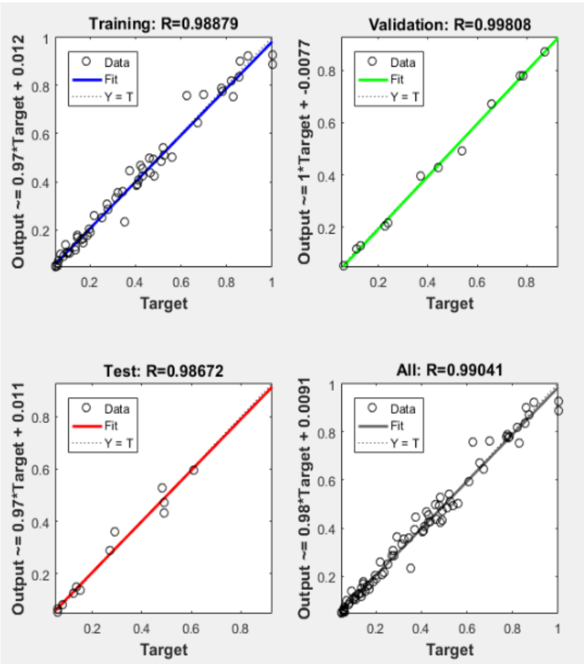

Fig. 3. Regression results of the best ANN model

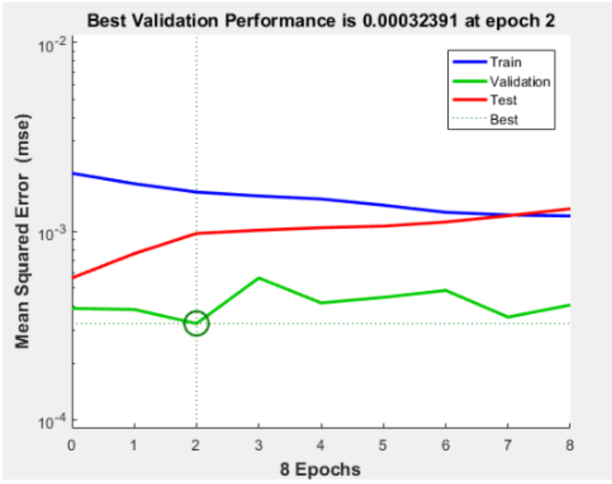

Fig. 4. MSE of Best ANN model

3. CONCLUSION

Turkey's renewable energy and thermal energy generation were estimated based on the gross electricity energy demand, population, gross domestic product and installed capacity indicators. The ANN model using the cascade-forward BP algorithm gave better results than the ANN modeled by the feed-forward BP algorithm, based on the model's test and verification results. In this study, with the ANN model how much will Turkey's future renewable energy sourced electricity and thermal energy power can be estimated as high as 98.35 % accuracy. In addition, this study is also important for Turkey’s future investments in energy.

Nomenclature

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMAX	Autoregressive Moving Average Exogenous
BP	Back Propagation
GDP	Gross Domestic Product
GEED	Gross Electricity Energy Demand
MSE	Mean Square Error

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