Electrical Energy Demand Forecasting Using Artificial Neural Network

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***Abstract*—The continuous development of technology, population growth, and increased economic comfort enlarge the energy demand. The welfare and economy of both the producer and the consumer need to meet the increasing energy need by making investments and planning with the correct predictions. In this study, the electricity demand forecast is made with the help of Artificial Neural Networks (ANN). In order to increase the accuracy, educational data sets were created with historical electricity consumption data, taking into account social, economic, technological, and demographic factors. The forecasting method developed was applied to Düzce, Turkey's developing provinces. The 15-year electrical energy demand of the region was estimated with the ANN-based method. The results have been evaluated in detail.**

Keywords—Artificial Neural Networks, Electricity Demand Forecasting, Load Forecasting Methods, Training Data Set

I.INTRODUCTION

The specific energy cost increase with the almost absence of fossil fuel in parallel with the increase in energy consumption. This increase has accelerated the search for new low-cost energy sources. The limited availability and significant ecological damage of fossil fuels have driven highly environmentally conscious people to cleaner and more sustainable renewable energy. Renewable energy sources can reduce line losses since the demand is generated and consumed near distributed generation facilities. Furthermore, excess energy can be stored for later use or sale. In this way, economic benefits are obtained for producers and consumers by providing high efficiency and low-cost energy. In case of an outage, it can contribute to the reduction of the difficulties experienced. The integration of distributed generation can reduce transmission losses, the effects of malfunctions and provide flexible energy usage by storing excess energy. DG can meet increasing energy demand more environmentally and economically using the existing network infrastructures, avoiding high-cost new installations.

Although the existing energy generation centers meet the consumption needs, they will become increasingly inadequate with the developments. Demand forecast (DF) is significant for high accuracy planning and correct operation of power systems. The renewable resource has been correctly selected and planned with the correct DF. The benefits will be increased by making suitable investments to benefit distributed generation. Excessive DF causes unnecessary cost, or underestimation causes inefficient investments, as the demanded power is not met.

The DF provides reliable, adequate, and wasteless energy to the consumers. In addition, future electrical energy planning is projected most appropriately in terms of location and size. In this study, the DF of the Düzce region has been made with Artificial Neural Networks (ANN), which are widely used recently. ANN is not linear, and it can reach the correct result by generalizing through learning the problem. The forecast error tolerance is high due to the spread information all connections ANN to be preferred for load prediction. The data set to be used in ANN is essential for the DF accuracy. Thus the load characteristics of the region, population, total electricity consumption per capita, Gross Domestic Product (GDP), net migration rate, East Marmara GDP, inflation, net migration, unemployment rate, electricity generation, annual population growth rate in Turkey and Düzce, electricity consumption factors data set. Electricity DF was made by bending ANN with the determined data set.

II.FORECAST MODELS

Electricity demands are very short-, short-, medium-, and long-term DF daily, weekly, and yearly. While estimating the load, the essential data and model selection factors are specified as time, weather, and economic factors [1].

The DF is generally collected under three headings in Singh's study: Traditional Forecasting Technique, Modified Traditional Technique, and Soft Computing Technique [2].

- Traditional Forecasting Techniques: It has enabled DF with the help of mathematical techniques. Traditional Forecasting Techniques can be listed as Regression Methods, Multiple Regression, Exponential Smoothing, and Iterative Reweighted Least-Squares.
- Modified Traditional Techniques: Adaptive DF, Stochastic Time Series, Support Vector Machine-based techniques are used to improve the prediction model under varying load conditions.
- Soft Computing Techniques: Soft Computing Techniques have been widely used in recent years by presenting an effective and efficient approach in systems where exact modeling is complex and uncertain. Genetic Algorithms, Fuzzy Logic, Artificial Neural Networks, Knowledge-Based Expert Systems can be given as Soft Computing Techniques [3].

III. ARTIFICIAL NEURAL NETWORKS

ANNs are simply mimicking the neural network structure of people with computer programs and finding solutions to problems in medicine, engineering, finance, and many other fields that cannot be solved with traditional techniques. The neural network provides the desired data in any area with a model that can accurately match input to output by using historical data. Training values created for the network are important factors in the correctness of the results obtained with ANN; otherwise, the network cannot meet the expected results.

Suppose we briefly mention the important features of artificial intelligence. In that case, it provides solutions without prior knowledge; it solves complex problems better than linear techniques because it is not linear. It is faster than alternative methods by including simultaneous identical and independent operations in parallel [4]. ANN consists of interconnected structures called neurons, and each neuron is a transfer function. A neuron is a nonlinear element with multiple inputs and single outputs. The formation structure of a neural network is determined by the connections and transfer processes of neurons in the network [5]. The correct selection of the function affects the network performance, and a clear output is obtained because it operates with the entered data.

Although artificial intelligence applications develop more and more every day, network structure and parameter selection, training values required for training the network, convergence, etc., problems are encountered. While the low number of hidden layers in ANN is insufficient in some solutions, the presence of too many hidden layers may cause undesirable results in ANN. Another problem is that it is unknown how many neurons are used; the most efficient result will be obtained. For this reason, the trial and error method is used for these problems in ANN.

The most widely used neural networks are MLF (Multilayer Feed-forward Neural Network) neural networks that operate on the backpropagation principle. The first layer is the entrance layer, and the last layer is the exit layer. The layers behind are hidden layers, and every neuron in any layer is connected to the neurons in the next layer. When the backpropagation network is turned, the input spreads forward from hidden, from hidden to output, and the weights are adjusted to minimize the error by calculating the error in the output layer. ANN structure consists of 5 parts: input layer, variable weight products, total function, activation function, and output.

In ANN, the relationship between neurons, with input values $\mathrm{X_n}$ in the external environment or other neurons, is specified with the weight coefficient specified as $\mathrm{W_n}$, and b is expressed as the threshold coefficient of the neuron. The threshold coefficient exists to prevent the neuronal elements' value and the network's output from being zero. The net output of ANN is y (1)

$$y = f\sum_{i=1}^{n}(X_i W_i + b) \tag{1}$$

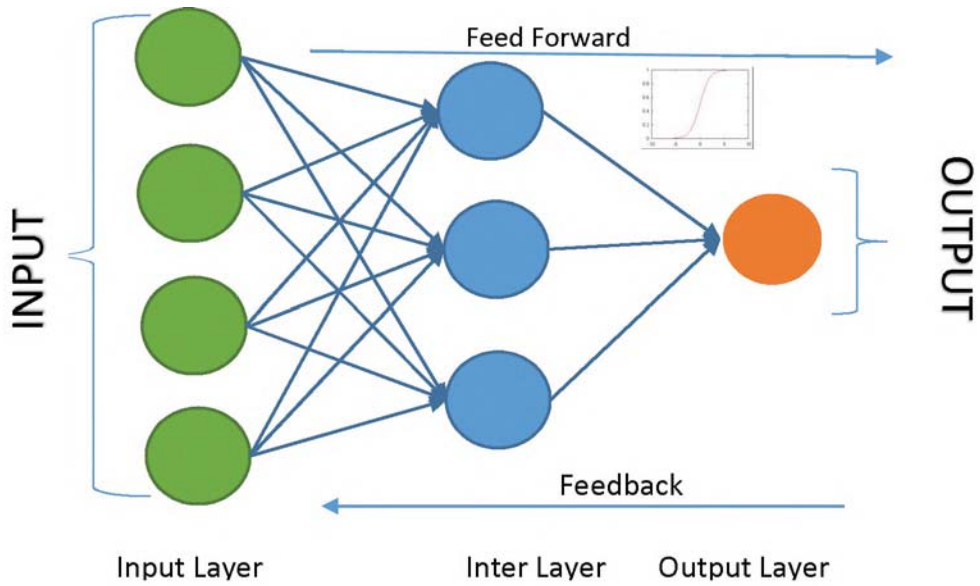

Figure 1. Single-input single-output ANN example

The sigmoid function is not a nonlinear monotonically increasing function that can be used with backpropagation algorithms because it is differentiable with an output value between 0 and 1. $f(x)$ including sigmoid function (2)

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

In the audited fit process, the threshold coefficient b and weighting coefficient W_n are changed to minimize the difference in squares between the calculated and required output values. This (3) is accomplished by equality. x_o and $\hat{x}_o$ computed and consisted of the necessary activities of the exit neurons.

$$E = \sum_{o}\frac{1}{2}(x_o - \hat{x}_o)^2 \tag{3}$$

The backpropagation algorithm is generally used by the gradient descent minimization method. The weight (5) and threshold coefficients between i and j neurons are (6) $(\lambda = learning\ rate)$ [6].

$$\omega_{ij}^{(k+1)} = \omega_{ij}^{k} - \lambda \left(\frac{\delta E}{\delta \omega_{ij}} \right)^{k} \quad (4)$$

$$b_{ij}^{(k+1)} = b_{ij}^{(k)} - \lambda \left(\frac{\delta E}{\delta b_{ij}} \right)^{k} \quad (5)$$

IV. LOAD FORECAST with ANN

Hayati and Shirvany have estimated the short-term burden for the Illam State located in the west of Iran between 2004-2006. They concluded with the improved ANN model that the least error, the best estimation can be made and can be an important tool for short-term DF [7]. In another study, Mitra and his colleagues used a feed-forward ANN and a backpropagation learning algorithm using data from the past months to forecast monthly inflation in India [6]. In another study, the performances of different ANN-based time series models have investigated for a 1-hour ahead forecast. Wind speed forecasts are made based on wind data sets from two observation sites in North Dakota. For each ANN model, the effects of different inputs and learning rates were examined in terms of multiple performance criteria. In addition, they noticed that different inputs and learning rates directly affect prediction accuracy [8].

S. Singh et al. used ANN to estimate the hourly short-term electrical load in the NEPOOL region (ISO New England). They obtained the MAPE (Mean Absolute Percent Error) value of 1.38% during the week and 1.39% at the weekend with separate analysis for the week and the weekend and stated that it was a good result for estimation [9]. In another study, day-ahead price estimation was made with feed-forward ANN. They obtained results using the last two years' data [10]. In another article, electricity DF was made using ANN to affect electricity consumption in railway transportation [11]. In another study, the power data of NARX (Nonlinear Automatic Regression Model) ANN was obtained from Belgium wind farms, and wind energy was estimated with the meteorological data required for wind speed. While it was stated that the wind energy estimation was accurate for some months, they found that the error in the estimation increased in April, May, and June 2014 [12]. Gautam et al. analyzed the short-term urban DF for the Roorkee region north of India (Uttarakhand state) in ANN. The load demand from the military, Madhopur, and Bharatnagar in the Madhopur region was the highest among the three areas mentioned in the study. They obtained the final results for every hour of each day for each of the three regions [13]. In another study, short-term national power estimation in Peru was tried by using direct and indirect methods.

The first method is regression models. The second method is based on ANN. They conclude that the ANN cumulative model is a fast, reliable, and accurate method to estimate the power demand in Peru [14]. In another study, it has been tried to provide weather-dependent electricity load profiles by using ANN for European countries. The output value of ANN represents the electricity demand at a certain hour of the year under defined weather conditions [15].

V.DATA SET and ANN ANALYSIS

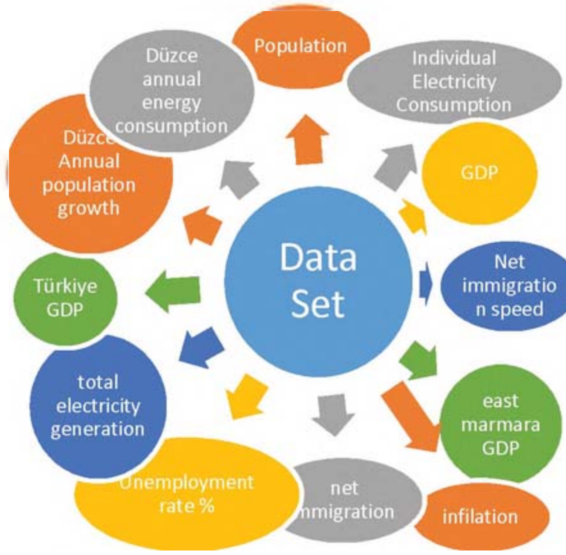

Figure 2. Data sets for ANN

The data set varies according to the study. Choosing the data set appropriate for the subject to be predicted is essential for the study's accuracy, and the incompatibility of the data set may cause the estimation results to become less accurate. Thanks to the data set prepared correctly, ANN can make proper inferences. In the study, the data set to find the result in the best way was created. Our network has been created with 2 layers as 1 hidden layer with 22 input nodes, 12 neurons and 1 output. Our network was trained with the Levenberg Marquardt algorithm in MATLAB, recommended by More and Jorge. TANSIG is used as a transfer function in the hidden layer. TRAINLM as training function, performance function MSE (Mean Squared Error). While creating our study, we chose values that will affect electricity consumption according to inflation and usage areas in the data set. The data set is shown in Figure 1.

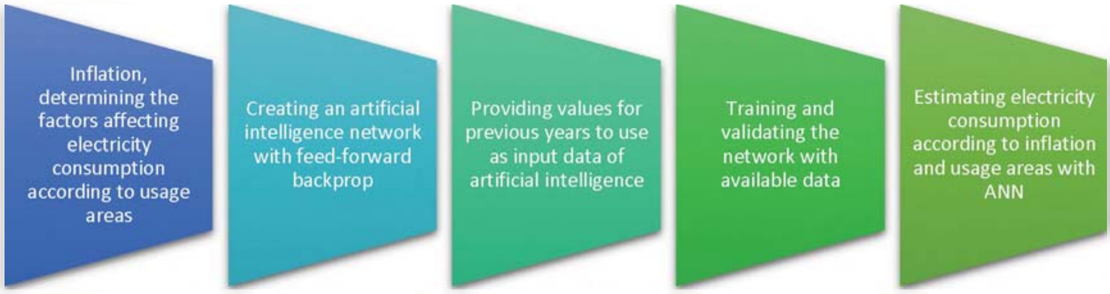

Figure 3. Steps applied to make predictions in ANN

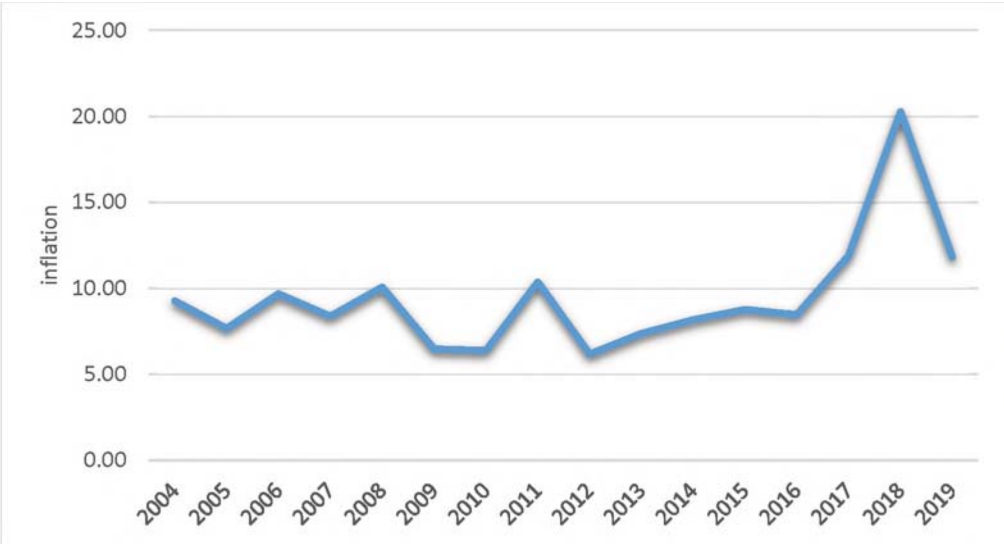

Figure 4. Inflation values between 2004-2019

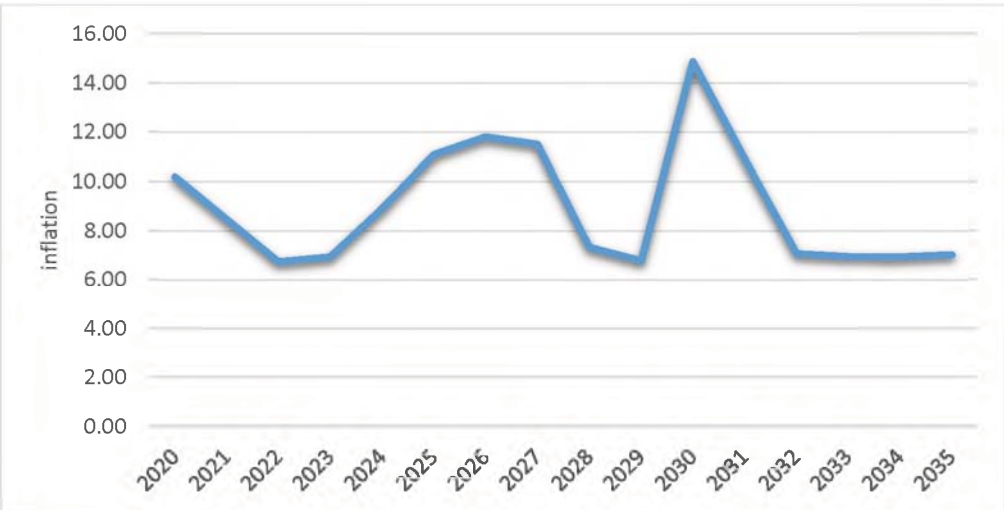

Figure 5. Forecasted inflations of 2020-2035

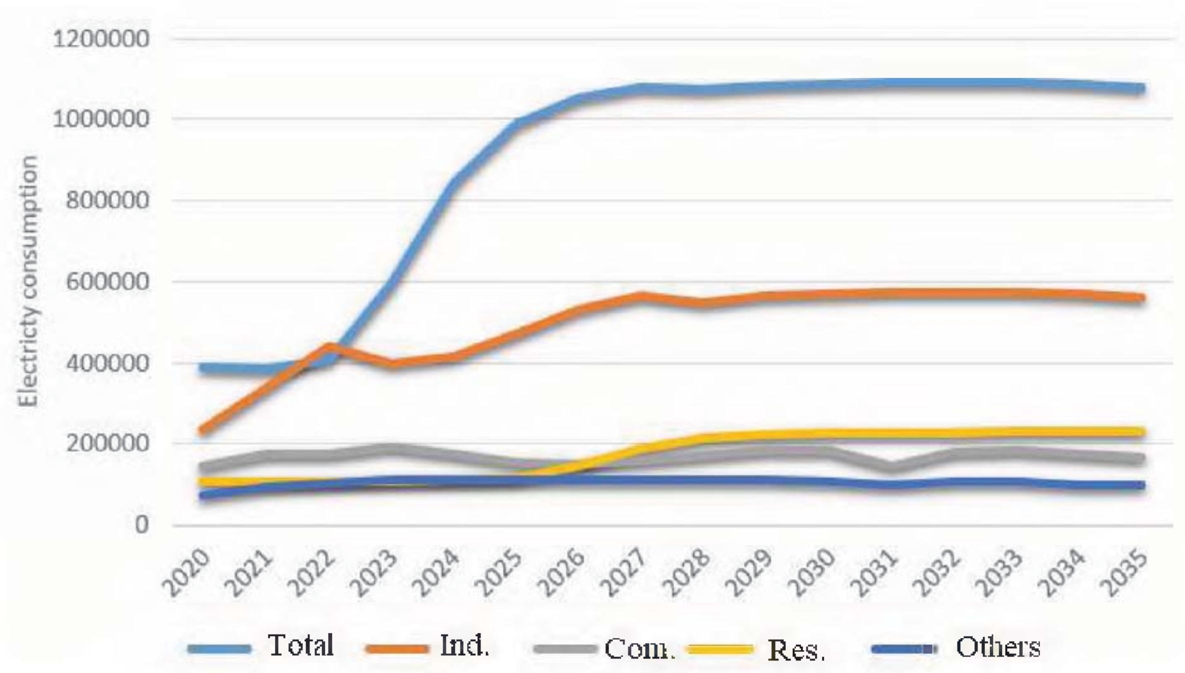

Figure 6. Electricity consumptions

In Figure 4, the inflation data of the data set between 2004 and 2019 was the lowest value of 6.20 in 2012, and it was stated as 20.30 in 2018. Figure 5, inflation estimation has been made in ANNs with the help of MATLAB for the next 15 years between 2020-2035, using the data of the factors that may affect inflation directly or indirectly, including inflation data from previous years. The result obtained because of the estimation is given in figure 5. Because of the simulation of inflation, it is concluded that inflation will see the lowest value in 15 years as 6.75 in 2022. It will see its highest value in 15 years in 2030 with a value of 14.89. Since inflation policy decisions may vary due to unforeseen reasons such as natural disasters in the country and legal regulations, making a 100% accurate forecast on inflation is difficult. However, close values were estimated by considering suitable conditions in this study.

The values of 15 years between 2004-2019 and the values in the data set are given in Figure 2. The DF of the 15-year including industrial, commercial, residential, and other electricity consumption (official, agricultural, street lighting, etc.) can be calculated with ANN in MATLAB. Figure 6 shows an overall increase in total electricity consumption, which increases the load. Suppose regional loads increase as a result of the simulation. In that case, various scenarios can be applied to meet the load in the region in the future.

VI. CONCLUSION and FUTURE WORKS

Accurate estimation of the increasing electrical energy demand in the rapidly developing world is essential for planning investments, economic calculations, and adapting quickly to change. In this study, a 15-year electricity demand estimation has been made considering the economic, demographic, environmental, electrical consumption, and social conditions of Düzce province. For ANN, the load characteristics of the region, population, total electricity consumption, GDP, East Marmara GDP, inflation, net migration, unemployment rate, electricity generation, Turkey and Düzce annual population growth rate, data on electricity consumption were determined as the data set for future estimation. Thus the ANN was trained; electricity DF and inflation forecasting were made.

As a result of the simulation, it was determined that the highest inflation would be in 2030, which is the 15-year forecasted years 2020-2035. However, it is challenging to determine inflation accurately due to unpredictable reasons. This study can be used in planning and investment decisions with various scenarios in line with electricity consumption estimate according to the area of use. It will provide economic benefits, especially in the size and positioning of environmentally friendly renewable energy plants, with DFs made taking into account the environmental and regional conditions. By developing a high-accuracy prediction model, it will be possible to make reinforcements for the existing power system infrastructure more accurately and at the right time. In addition, as the management and control of the DG facilities to be established at the consumption points will be done more healthily, the power system management will be easier.

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