ARTICLE IN PRESS

Journal of Engineering Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Engineering Research

journal homepage: www.journals.elsevier.com/journal-of-engineering-research

Electricity consumption estimation with differential polynomial and artificial neural networks: Case of Türkiye

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ARTICLE INFO

Keywords:
"Differential polynomial neural networks"
"artificial neural networks"
"electricity"
"consumption estimation"

ABSTRACT

Electrical energy is one of the indicators that express the welfare and modernization level of countries. It is a type of energy that needs to be consumed as soon as it is produced and is cumbersome to store. For this reason, the estimation accuracy of the consumption demand is important in order to meet the supply. In this study, Artificial Neural Networks (ANN), which are frequently used in applications, and Differential Polynomial Neural Networks (D-PNN), a new type of neural network, are compared in the electricity consumption estimating problem. While comparing the methods, the independent variable data of exports, imports, population, installed power, and gross domestic product were used as the inputs of the models, and the electricity consumption values of Türkiye in a certain time interval were estimated. As a result of the comparisons, it was seen that the D-PNN method gave good results in performance criteria, ranging from 52.5% to 58.8%, compared to ANN.

1. Introduction

Energy, which is the determining factor of social, geographical, and economic welfare for the coming years and directs world politics, is especially important for the welfare of developing countries [1]. At the same time, energy is the factor that determines both political and economic competition between countries. Being a competitive element increases the importance of energy and the awareness of states in the field of energy [2]. Electrical energy, which is one of the energy types, is the most determinant of the welfare level due to the prevalence of use. Electrical energy is an energy source that cannot be stored and must be consumed as soon as it is produced. Considering the current account deficit values of energy-dependent European countries such as Türkiye, the contribution of annual electrical energy is quite large. Since electrical energy cannot be stored, it must be supplied according to demand. For this reason, high-accuracy estimation of the demand is important both for meeting the sufficient demand and for the energy policies of the country. Estimation studies for electrical energy, which is of critical importance for our country, started in the 1960 s [3]. The aim of the planning made for the increasing demand for electricity with the increasing population, technological developments and rapid industrialization is to provide the future demands in the most economical, reliable, and quality way. For this, it is aimed to obtain more accurate prediction values by developing the most accurate estimation system with the factors affecting the electrical energy consumption of each country.

When demand estimating studies on electrical energy are examined, there are studies with different methods and variables in the literature. Srinivasan [4] made a comparative evaluation of various traditional and neural network-based methods to estimate demand in six categories of residential, industrial, non-commercial, non-industrial, recreational, and public electricity data, and concluded that neural network-based models yielded better results. Geem and Roper analyze South Korea's energy demand with an error backpropagation algorithm and feed-forward multilayer sensing (FF-BP-ANN) artificial neural network model with four independent variables such as gross domestic product (GDP), population, imports, and exports. The results obtained by making estimation studies were compared [5]. Pao has estimated the electricity and petroleum energy, which constitute almost 90% of the total energy consumption in Taiwan, by presenting a hybrid nonlinear model with these two models [6]. Bilgili, using linear regression (LR), non-linear regression (NLR), and artificial neural networks (ANN) methods, using Türkiye's electricity consumption and installed capacity, gross electrical energy production, population, and the total number of subscribers between 1990 and 2007. In the estimation study, it was seen that the performance value of the ANN method obtained better results than the LR and NLR models [7]. Demirel

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https://doi.org/10.1016/j.jer.2023.100073
Received 2 March 2023; Received in revised form 11 April 2023; Accepted 12 April 2023

et al. evaluated the performance of these two models by estimating the annual electrical energy load of Türkiye until 2010 with Adaptive Network Based Fuzzy Inference System and Autoregressive Moving Averages models [8]. Yigit has made an estimation of Türkiye's annual electrical energy consumption until 2020 based on the independent variables of gross domestic product (GDP), imports, exports, and population, using the Genetic Algorithm. The results obtained showed that both models based on quadratic and linear gave effective results [9]. Chang et al. developed the weighted fuzzy neural network approach and estimated the electricity demand of Taiwan and questioned the applicability of the developed method with the obtained results [10]. Ardakani and Ardehali estimated the electricity consumption demand of America using the best artificial neural network based on particle swarm optimization (IPSO) and scrambled frog jump (SFL) algorithms. The obtained results showed that the IPSO-ANN model gave better performance [11]. In another study, Ardakani and Ardehali made the prediction of long-term electricity demand by developing optimized regression and artificial neural network models based on gradient-ordered descent (GD), particle swarm optimization (PSO), and enhanced particle swarm optimization (IPSO) methods. It has been understood that the electrical energy consumption estimates based on the IPSO-ANN model and socio-economic historical data give the most accurate results [12]. Kaytez et al. estimated Türkiye's electricity consumption using regression analysis, artificial neural networks (ANN), and least squares support vector machines (LS-SVM). The obtained results showed that the proposed LS-SVM model was more successful [13]. Berneti, combined a genetic algorithm, to develop an Adaptive Network-Based Fuzzy Inference System (ANFIS) for electricity consumption estimation. In the model he developed, he tested the method by estimating Iran's electricity demand. The results obtained proved that the developed hybrid model was more effective [14]. Başoğlu and Bulut proposed the EPSİM-NN system, which is a hybrid study of expert systems and artificial neural networks, and evaluated the system by estimating Türkiye's electricity demand [15]. Details of the studies carried out using the artificial neural network method for electricity demand estimating are given in Table 1.

In this study, unlike other studies in the literature, Türkiye's electrical energy demand is estimated by modeling with a different type of neural network, differential polynomial neural networks. The results obtained with D-PNN were compared with the results of artificial neural networks in terms of various performance indicators.

2. Methodology

2.1. Differential polynomial neural networks

A differential polynomial neural network (D-PNN) is a network system for finding the best solution using fractional differential multi-parametric polynomial functions based on learning according to the functionality of the human brain. It acts as a brain mechanism in identifying unknown relationships. Thus, it has the opportunity to define the data range of different sizes by processing it better. In addition, the highly dynamic behavior of neurons, which is one of the characteristics of the network, also affects its activation [16]. A differential polynomial neural network is a different type of neural network from artificial neural networks. In a systematic sense, differential polynomial neural networks construct and also solve the unknown general partial differential equation of the function using multivariate complex and nonlinear polynomials. This systematicity can be seen as a simulation of the learning of the human brain as it explores the dependency generalization of the input data [17].

The Group Method of Data Handling (GDMH), developed by Aleksey Ivakhnenko in 1968 for neural network structure design and setting parameters of polynomials, is the starting point of the differential polynomial neural network. The operating and design principles of differential polynomial artificial neural networks are different from GMDH based on Taylor series extensions, but it breaks down the

Table 1
Studies for estimating electricity demand.

Authors	Estimation method	Variables	Data	Year of data	Training	Test
Srinivasan (Srinivasn 2008)	Artificial neural networks	Time, consumption	Monthly	78 months	66 months	12 months
Geem and Roper (Geem and Roper 2009)	Artificial neural networks	GDP, population, import, export, consumption	Yearly	1980–2006	1980–2000	2001–2006
Pao (Pao 2009)	ANN + SEGARCH, ANN +WARCH	Time, consumption	Monthly	1993–2007	1993–2005	2006–2007
Bilgili (Bilgili 2009)	ANN, linear regression, and nonlinear regression	Installed capacity, population, number of subscribers, electricity generation	Yearly	1990–2007	1995–2007	1995,2000,2005
Demirel et al. (Demirel et al. 2010)	Adaptive network-based fuzzy inference system and autoregressive moving averages	GDP, energy produced, installed power, population	Yearly	1970–2007	-	-
Yiğit (Yiğit 2011)	Two new methods based on genetic algorithm	GDP, import, export, population	Yearly	1979–2009	-	-
Chang et al. (Chang et al. 2011)	Weighted evolving fuzzy neural network	Air pressure, temperature, wind speed, rainfall, rainy time, humidity	Monthly	1997–2006	1997–2004	2005–2006
Ardakani and Ardehali (Ardakani and Ardehali 2014a)	IPSO-ANN and SFL-ANN	GDP, time, import, export, population	Yearly	1967–2009	1967–2001	2002–2009
Ardakani and Ardehali (Ardakani and Ardehali 2014b)	Regression and ANN models based GD, PSO, and IPSO	GDP, time, import, export, population	Yearly	1967–2009	1967–2001	2002–2009
Kaytez et al. (Kaytez et al. 2015)	ANN, least squares support vector machines and regression analysis	Electricity production, number of subscribers, population, installed capacity	Yearly	1970–2009	1970–1996	1997–2009
Berneti (Berneti 2016)	Adaptive network-based fuzzy inference system, GA	GDP, number of customers, electricity price, import, export	Yearly	1967–2011	1967–2011	1967–2011
Başoğlu ans Bulut (Başoğlu and Bulut 2017)	Expert systems + ANN	Previous day, feast days, temperature	Daily, Weekly	2005–2016	2005–2015	2016

general partial differential equation into GMDH as in the general input-output coupling polynomial [17]. D-PNN constructs and solves the general partial differential equation (DE) by modeling a sought functionusing the substitution combination of unknown and generally partial multivariate polynomial derivative terms (Eqs. 1–3)[16,18].

$$y = a_0 + a_1x_i + a_2x_j + a_3x_ix_j + a_4x_i^2 + a_5x_j^2 \tag{1}$$

Where $x_{(i)}$ is the input variables and $a(a_0, a_1, a_2, \ldots, a_n)$ is the parameter vectors.

$$Y = a + bu + \sum_{i=1}^{n} c_i \frac{\partial u}{\partial x_i} + \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} \frac{\partial^2 u}{\partial x_i \partial x_j} + \ldots = 0 \tag{2}$$

$$u = \sum_{k=1}^{\infty} u_k \tag{3}$$

Where $u = f(x_1, x_2, \ldots, x_n)$ is the searched function of n-input variables, a, $B(b_1, b_2, \ldots, b_n)$, $C(c_{11}, c_{12}, \ldots, c_{mn})$ the parameters.

D-PNN output is obtained by dividing the active neuron output values of different numbers of neurons, which vary according to the problem in the network, by the number of active neurons, that is, by the terms of the differential equation, and taking the arithmetic average (Eq. 4).

$$Y = \frac{\sum_{i=1}^{k} y_i}{k} \tag{4}$$

Where k is the actual number of active neurons. Y is the overall D-PNN output.

Basic structural elements of differential polynomial neural network; the input variables, blocks, neurons, hidden layers, and outputs. The smallest unit of operation is the blocks in which the equations in the system are formed and turned into neurons. Fig. 1 shows the block structure.

D-PNN, which has a multilayer and backward working mechanism, can only combine two inputs in each block, so it creates composite polynomial functions that represent higher combinations of input variables in substitution differential equation (DE) terms. Fig. 2 is a cross-section of the working mechanism of the D-PNN system. As can be seen in Fig. 2, two input variables in each block, a reverse working mechanism with binary combination and the interaction of input-output variables, resultant functions, in other words, neurons are formed. In the equation y_5 formed in the 1st block of the 3rd layer in Fig. 2, 5 simple neurons were formed. The differential polynomial neural network can use sigmoid transformations in all polynomials.

2.2. Artificial neural networks

Artificial neural networks are a kind of artificial intelligence technique used to model and solve complex problems based on the working logic of biological nerve cells, which are the main components of the human brain. It has a structure that learns by establishing meaningful relationships between inputs and outputs and produces outputs by generalizing from new inputs. While the learning process in the human brain is carried out with biological neurons, artificial neural networks perform this process with artificial neurons [19]. Just like a human, the output quality of an artificial neural network is directly proportional to the quality of the training process.

The most basic information processing unit of artificial neural networks is artificial neurons. The connection of artificial neurons with each other is done in layers. The layers are provided by interlayer connection by grouping them as the input layer, where the data set is introduced, the hidden layer where the data from the input layer is processed with an appropriate function, and the output layer in order to prevent the neurons from being stacked (Fig. 3).

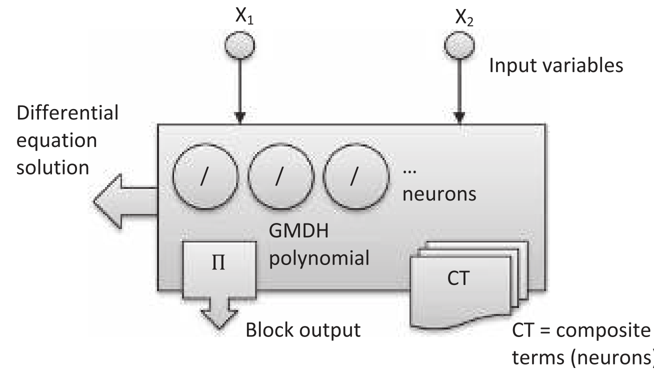

Fig. 1. A block consisting of neurons(ie substitution derivative terms) [18].

Inputs are transformed into outputs by subjecting them to a number of functions in each neuron in the layers, and the network parameters are updated to reduce the error by controlling the difference (bias) between the obtained outputs and the actual outputs. This process is repeated continuously to create a network architecture that produces realistic output values. ANN is widely used in the literature for the prediction of many phenomena such as temperature and precipitation variations, solar photovoltaic power generation, weather, etc [20–22].

2.3. Statistical evaluation methods

Among the statistical evaluation methods in the comparison of the results of D-PNN and ANN; root mean square error (RMSE), mean absolute percent error (MAPE) and correlation coefficient r were used. The RMSE and MAPE indicators are used to analyze how far the predicted values spread from the true values (Eq. 5, Eq. 6). The correlation coefficient r is used to express the degree and direction of the relationship between two variables (Eq. 7).

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|Y_i - F_i|}{Y_i}}{n} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - F_i)^2} \tag{6}$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{7}$$

Here, n denotes the number of data that will enter the calculation, Y_i the actual values, and F_i the predicted values. $\bar{x}$ and $\bar{y}$ represent the mean of the variables.

3. Application

3.1. Preparation of data set and analysis

Considering the studies examined in the literature section on the subject, population, import, export, GDP, and installed power criteria are considered independent variables in practice. The amount of energy consumption varies according to the changes in the population. Changes in import and export quantities are important in terms of showing the electricity usage performance of the country in the production and consumption processes. Gross domestic product (GDP) is important in terms of reflecting economic growth. As a country's GDP increases, electricity usage rates are expected to increase. Installed power is one of the important factors used in the estimation of consumption, as it affects electricity production and thus consumption. The data of the variables used in the study belong to the values of the Turkish Statistical Institute (TSI 2017)

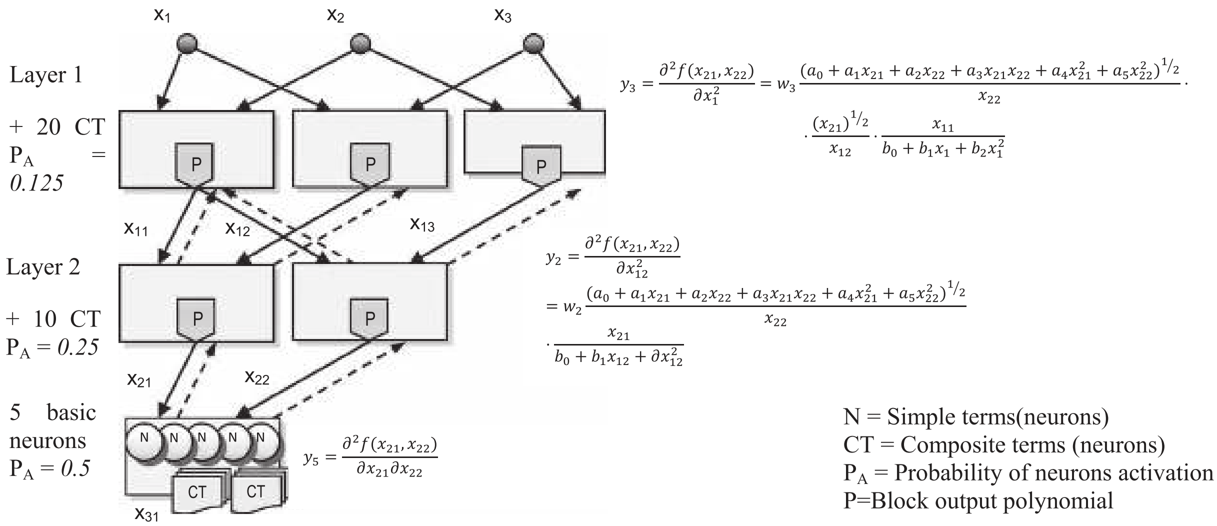

Fig. 2. Composite function formation with backward connections[18].

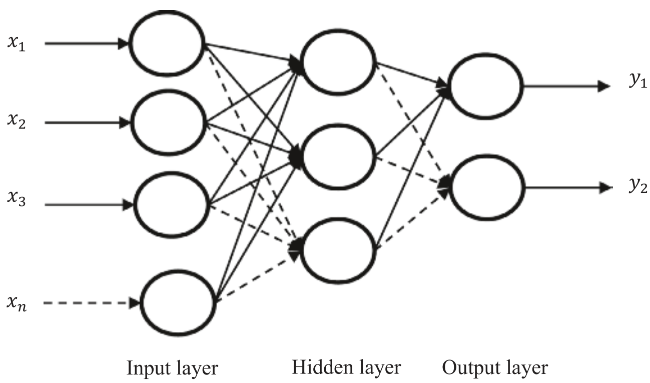

Fig. 3. The basic structure of artificial neural networks.

Table 2
Sources of data used in the study.

Variable	Sources
Population	TSI
Imports	TSI
Exports	TSI
GDP	TSI
Installed power	TETC

and the Turkish Electricity Transmission Company (TETC 2017) between 1965 and 2016 (Table 2) [23,24].

Before applying the techniques, the degree of relationship between the independent variables and the dependent variable electricity consumption data was calculated according to Eq. 7 (Table 3).

Table 3
The correlation coefficients between electricity consumption and input variables.

	Installed power	Population	GDP	Exports	Imports
r	0.99	0.95	0.97	0.96	0.95

When the results are examined, it is seen that the independent variables to be used as inputs have a high and positive correlation with the electricity consumption values. This will positively affect the quality of the estimation results of D-PNN and ANN applications, where variables will be evaluated together.

3.2. Application of D-PNN and ANN

The values of the variables used in the application were normalized for both methods. 37 pieces of data belonging to the years 1965–2001 are reserved for the training of networks and 15 pieces of data belonging to the years 2002–2016 are reserved for testing. In the input layer of both network architectures, there are import, export, GDP, population, and installed power independent variables defined to the network. In the output layer, there is a single block (electricity consumption). The most suitable network parameters for both network structures were found by trial and error and the networks were compared by running them over these parameters. Estimated electricity consumption values obtained from D-PNN and ANN models over the test set are given in Table 4 and Fig. 4.

The performance of both methods in the test set was compared over RMSE and MAPE values. Obtained results are shown in Table 5. The

Table 4
Actual and estimated consumption values of Türkiye's electricity energy.

Years	Actual (GWH)	ANN Estimates (GWH)	D-PNN Estimates (GWH)
2002	132,553	128,010	138,691
2003	141,151	143,189	143,786
2004	150,018	146,748	147,819
2005	160,794	150,005	158,572
2006	174,637	163,442	169,057
2007	190,001	163,586	192,046
2008	198,085	184,381	210,735
2009	194,079	181,276	197,276
2010	210,434	193,211	222,535
2011	230,306	210,992	233,472
2012	242,370	217,305	241,035
2013	246,357	228,663	251,168
2014	257,220	232,194	254,483
2015	265,724	244,633	250,790
2016	279,286	248,087	258,043

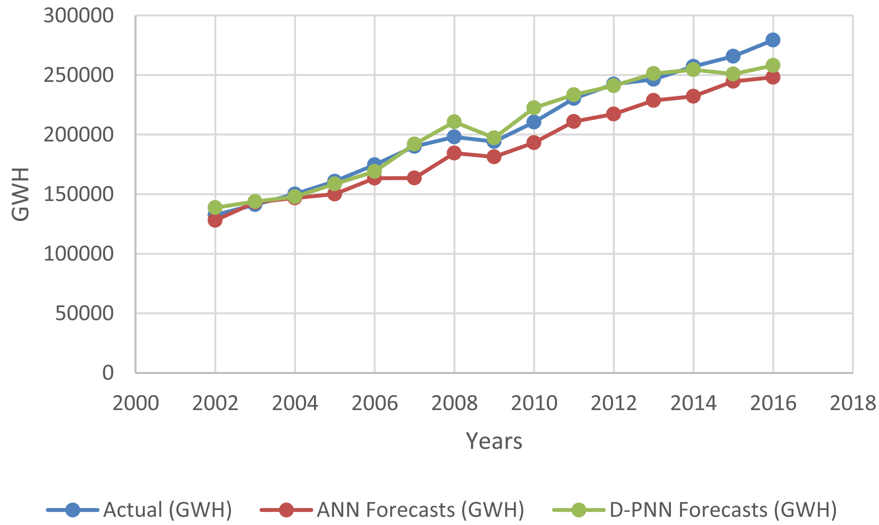

Fig. 4. Comparison of D-PNN and ANN results with actual values.

Table 5
Statistical results of D-PNN and ANN models.

	RMSE	MAPE (%)
D-PNN	8653	3.04
ANN	18225	7.37

values obtained from the measurement of the values obtained as a result of the application with the actual values are included.

4. Conclusion

Electrical energy is one of the main factors reflecting the country's economy and development. The fact that it cannot be stored necessitates accurate estimates of electrical energy. In particular, the fact that our country, due to its location, mainly meets the electrical energy resources with exports and has a significant share in the current deficit, increases the importance of maintaining the balance between supply and demand in energy. The accuracy of the estimates will directly affect the validity of the planning studies and will ensure the correct management of the supply-demand relationship. For this reason, estimating is very important in order to meet the demand in the energy sector in an economical way.

In this study, Türkiye's electrical energy consumption estimation was made with differential polynomial neural networks and artificial neural networks. The independent variables of GDP, imports, exports, installed power, and population between 1965 and 2016, which affect electrical energy consumption, are used. The data for the years 1965–2001 were used as training data, and the data for the years 2002–2016 were used as test data. When the results were examined, it was seen that the results obtained with the D-PNN method were better than the results obtained with ANN. It gave 52.5% better results in RMSE and 58.8% better in MAPE. As a result of the study, it has been seen that the D-PNN method can achieve better results in estimation studies where the number of data such as annual energy consumption data is low. This shows that the D-PNN technique can be preferred in similar estimation studies with fewer data.

Funding

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

We thank Ladislav Zjavka for his support for the study.

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