Computers and Informatics
2757-8259 2022, Volume 2 Issue 1
Research Article

The estimation of electrical energy consumption using Artificial Neural Networks

Fatih Baltacı
Kahramanmaraş Sütçü İmam University, Directorate of Construction and Technical Works, Kahramanmaraş, Türkiye
Ali Öter
Kahramanmaraş Sütçü İmam University, Department of Electronics and Automation, Kahramanmaraş, Türkiye
alioter@ksu.edu.tr

Submitted: *05.05.2022*
Accepted: *07.06.2022*
Published: *30.06.2022*

Abstract:

In today's world, as a result of technological developments, electrical energy occupies a vital position in daily human life and industrial applications. In recent years, various methods have been used for the estimation of electrical energy generation and consumption. Similarly, the present study benefits from artificial neural networks for the estimation of electrical energy consumption. Artificial neural networks are one of the most widely applied and studied methods in many different fields. In the present study, electrical energy consumption values of a public institution for 6 years between 2016 and 2021 were used to compare the performances of different artificial neural network structures based on two criteria: mean absolute percent error and mean squared error. In addition, prospective electrical energy consumption values in 2022 and 2023 were also estimated.

Keywords: *ANN, Electrical energy, Estimation of electrical energy consumption, Mean Absolute Percent Error, Mean Squared Error*

Cite this paper as:	Baltacı, F. & Öter, A. The estimation of electrical energy consumption using Artificial Neural Networks, *Computers and Informatics*, 2022, *2*(1), 14-20.

1. INTRODUCTION

Human needs for energy are increasing day by day due to the developing technology, which brings about major problems such as ecological deterioration, high inflation rates, resource depletion, budget deficit and external dependency. In recent years, wars around the world and economic crisis have required nations to facilitate and maintain their economic growth in the future. For a healthy economic growth, it is always necessary for nations to continue production. One of the most crucial components of production is electrical energy.

A government is expected to supply high quality, reliable and sustainable electrical energy for their citizens, organizations and businesses. Since it is not possible to store electrical energy (EE) due to direct consumption, it bears utmost importance to implement precise production planning and management. It is also critical for businesses, organizations and individual users to plan their respective EE consumption. In addition to a nation's external dependency for EE for EE generation, constantly increasing EE consumption costs make it inevitable for all consumers to estimate and calculate their consumption figures. However, the estimation of future EE consumption is a challenging task for consumers, as it requires to take various factors into accounts such as sudden power cuts, power failure and holidays. Based on a consumer's specific needs, it is possible to perform daily, weekly, monthly and annual estimation of EE consumption. Because of high energy costs in today's world, the estimation of EE consumption (EEEC) occupy an important position in a consumer's future budget planning. EEEC may significantly vary depending on power outages, changing climate conditions or different consumer behaviors. As a result, an effective EEEC method for a consumer may not be feasible for another consumer.

There are many studies on the EEEC in the existing literature. These studies may be divided into three categories, as they usually focus on a certain city, energy region or the whole country. For instance, in 2003, Karacasu analyzed long-term load estimation for the province of Gaziantep via artificial neural networks using moving average and least squares methods [1]. In 2011, Toker and Korkmaz benefited from advanced signal processing techniques and artificial neural networks (ANN) for the hourly estimation of short-term EE demand in Turkey [2]. In another study, Tekin estimated EE demand in Mersin until 2023 using ARIMA algorithm [3]. Similarly, Kocadayı et al. conducted a study on annual EEEC in TR81 energy region [4].

The present study aims at EEEC using ANN based on the EE consumption data obtained from a public institution between 2016 and 2021. It was observed that the proposed method achieved a highly accurate EEEC when compared with the actual consumption data. The performance of the proposed method was analyzed by calculating Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE).

2. MATERIAL AND METHODS

2.1. The Obtained Data

The data were collected from EE consumption values in KSU Avşar Campus between January 2016 and December 2021. The distribution of EE consumption data in kilowatt-hour (kWh) is given in detail in Table 1.

Along with complex seasonal variations, the EEEC also involves linear relationships. Because these variations may differ within a certain time period, when analyzing the obtained signal, it is often important to take daily, monthly and seasonal variations into consideration. In addition, the duration of a time period for which EEEC will be perform is also critical. In particular, EEEC for future data require establishing a direct correlation with consumption data in the past. The highest EE consumption data were observed in August in 2016 and 2017, whereas it was in July in 2018 and 2019.

Table 1. Monthly EE consumption data (kW).

Month	2016	2017	2018	2019	2020	2021
January	484180.40	524787.00	540578.40	593666.10	597822.12	499906.26
February	418761.80	462717.10	501761.30	476511.10	658741.86	437134.95
March	442012.20	467218.90	473384.90	480761.90	509192.46	476703.99
April	333692.40	362778.50	361537.50	395417.50	280166.04	341211.15
May	398094.90	270248.30	393837.70	379813.30	302234.94	312474.33
June	563265.90	496236.50	498833.70	524707.20	590783.13	599884.74
July	637852.20	715953.10	753294.90	741662.90	851802.21	843808.77

August	826404.30	733006.30	619462.70	659014.20	703700.55	915247.62
September	521148.60	729585.00	627090.00	635851.80	719739.72	707226.03
October	483779.50	461000.00	442195.60	500443.50	489258.63	411556.32
November	488131.20	446253.70	454072.60	455496.30	412740.09	527655.24
December	568703.50	550534.80	524496.20	579944.61	498373.47	699456.87

2.2. Data Normalization

Data normalization can be defined as the reorganization of numerical data in a given dataset based on a common scale without disrupting significant differences in a value range. Its main objective is to reduce data size and thus obtain simpler and more meaningful results that can be interpreted in a quicker way [5, 6]. In the current literature, data normalization is performed through several methods such as decimal scaling, Z-score and minimum-maximum (Min-Max) [7]. Min-Max data normalization method was used in the present study.

In an ANN, it is necessary to convert values to a range of 0 and 1, which is also called normalization. In this process, the highest consumption is assigned a value of 1, whereas the lowest consumption value is 0. The normalization formula can be defined as follows:

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin} \tag{1}$$

X_{norm} is the normalized value, x is the actual consumption value, X_{min} is the minimum normalized value, and X_{max} is the maximum normalized value. EE consumption data were normalized using Eq. 1, and the obtained values are presented in Table 2.

2.3. Artificial Neural Network Model

ANNs are widely used in many different fields such as finance, factory management, automated control, troubleshooting, medical technology, military technology, communication, production, automotive, aircraft, space technology, speech and voice analysis, character and image recognition and security [1, 2, 6].

In recent years, ANN has been a popular modelling technique in scientific research. As for the classification of complex data, ANN is widely used in different applications such as image recognition, classification, system modelling, function convergence and prediction of chaotic time series [6, 8]. Introduced by Werbos and developed by Parker, Rummelhart and McClelland [9,10], backpropagation network is an ANN. The selection of activation function in an ANN network relies in ANN term. Therefore, the derivative of an activation function must be effectively calculated. The number of hidden layers and number of neurons in a hidden layer in an ANN usually depends on the problem which will be applied to the network. A hidden layer and output layer calculate the sum of weighted inputs. Nowadays, sigmoid function or hyperbolic tangent function are usually among the most commonly used activation functions [7, 11]. Although a higher number of neurons in a hidden layer leads to complex computations and, not surprisingly, a longer computation time, it also facilitates the use of an ANN model in the solution of more complex problems. An output layer produces the network outputs after the information is given to the input layer and processed through interlayers. These outputs are given as the external network information. The structure of a feedforward ANN is shown in Fig. 1.

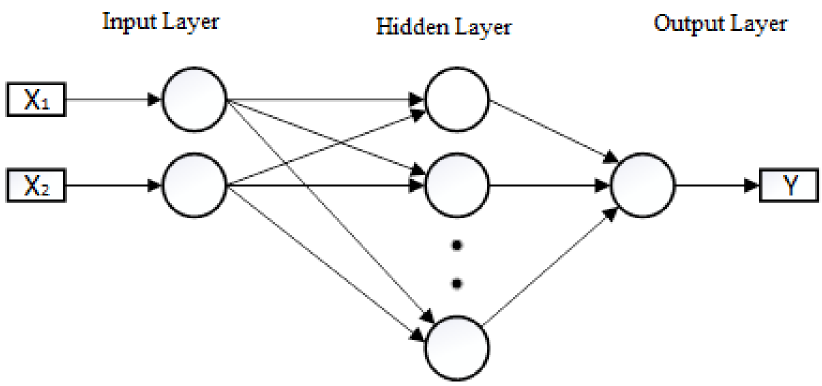

Figure 1. Feedforward ANN structure.

Each input in the input layer is fed into each node in the hidden layer and other nodes in the output layer. It must be noted here that the number of nodes may varies for each layer and that the data will pass through two or more hidden layers prior to the output layer. In this respect, it is of vital importance to optimize the neural network for a certain problem and thus to select the number of nodes and layers accurately [11]. As shown in Figure 2 above, the model is called a feedforward network because signals pass through neutral network layers in a single direction. However, neural networks are not limited to this model, since there are also feedback neural networks which allow signals to pass through in both directions.

During its training process, an ANN calculates the output corresponding to input values. The difference between the intended output and calculated output is used to update weights in ANN thanks to backpropagation algorithm. This process is called ANN training or optimization. The weights are constantly updated until an optimal performance rate is achieved.

2.4. Performance Criteria

Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) were used to reveal any significant differences between the EEEC and actual EE consumption data. According to Lewis, the accuracy rate of a MAPE range may vary, as 10% or lower is highly accurate, 11% to 20% is good, 21% to 50% is reasonable, and, finally, 51% or higher is inaccurate [12]. According to Witt, on the other hand, a MAPE value lower 10% is highly accurate, whereas a value between 10% and 20% is accurate [13]. The mathematical calculation of a MAPE value is given in Eq. 3.

$$e^t = x_t - y_t \tag{2}$$

x_t is the actual consumption in a period of t, y_t is the estimated value in a period of t, n is the number of estimated periods, and e^t is the estimation error.

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e^t|}{x_t}}{n} 100(\%) \tag{3}$$

Mean Squared Error is an indicator of convergence between the estimated and calculated values. A lower MSE is directly proportional to an accurately estimated value. Therefore, a higher MSE value indicates a larger gap between the estimated and actual value. The mathematical calculation of a MSE value is given in Eq. 4 [14,15].

$$MSE=\frac{1}{n}\sum_{t=1}^{n}\left(x_{t(actual)}-y_{t(estimated)}\right)^2 \quad (4)$$

3. RESULTS AND DISCUSSION

Normalized monthly consumption values for ANN are used for input in our study. As for the normalized data, the highest and lowest consumption value is 0 and 1, respectively. Eq. 1 was used to normalize annual EE consumption data for each year, and the obtained normalized consumption data are given in Table 2.

Table 2. Normalized EE consumption data.

Month	2016	2017	2018	2019	2020	2021
January	0.33167	0.39463	0.41911	0.50142	0.50786	0.35605
February	0.23025	0.29840	0.35893	0.31978	0.60231	0.25873
March	0.26630	0.30538	0.31494	0.32637	0.37045	0.32008
April	0.09836	0.14345	0.14153	0.19406	0.01537	0.11002
May	0.19821	0	0.19161	0.16986	0.04959	0.06546
June	0.45429	0.35036	0.35439	0.39451	0.49695	0.51106
July	0.56992	0.69101	0.74891	0.73087	0.90163	0.88924
August	0.86225	0.71745	0.54141	0.60273	0.67201	1
September	0.38899	0.71215	0.55324	0.56682	0.69688	0.67748
October	0.33105	0.29573	0.26658	0.35689	0.33955	0.21908
November	0.33780	0.27287	0.28499	0.28720	0.22091	0.39908
December	0.46272	0.43455	0.39418	0.48014	0.35368	0.66544

A multilayer feedforward ANN model was used in the present study. It consisted of a single-cell input layer, 12-cell hidden layer and a single-cell output layer. In addition, hyperbolic tangent function was used as the activation function in this model, since it is a suitable choice in order to divide a dataset into two groups for the classification process. The expected output values must also be suitable to these output layers.

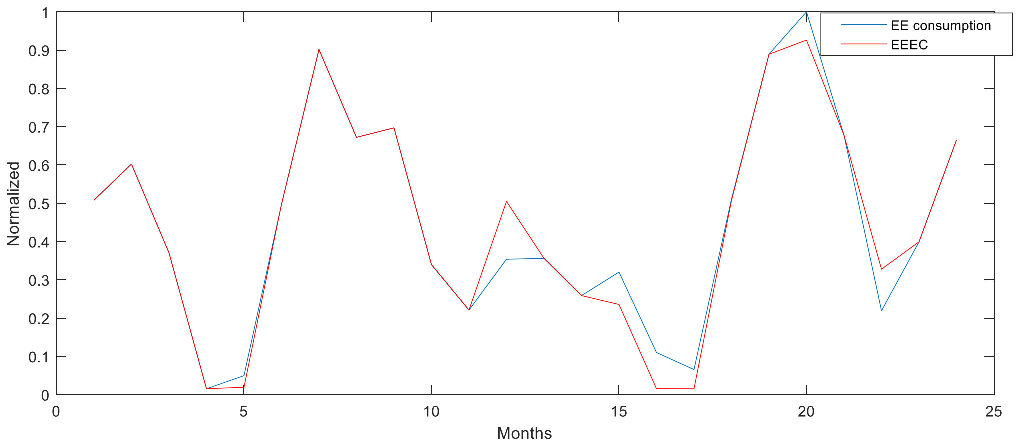

Figure 2. The EEEC and actual EE consumption data for 2020-2021.

In the present study, 48-month EE consumption data between 2016 and 2019 were used to train ANN. In addition, the EEEC data were also collected for 2020-2021 period. The graphs of the EEEC and actual EE consumption data for 2020-2021 period are shown in Fig. 2.

Table 3. The normalized and converted estimation data.

Month	2020 Normalized	2021 Normalized	2020 Estimation	2021 Estimation
January	0.507867022	0.356059281	597822.18	499906.29
February	0.602316397	0.258739292	658741.97	437134.97
March	0.370456526	0.235536149	509192.51	422168.96
April	0.015389503	0.015550298	280174.52	280278.23
May	0.019275108	0.015381309	282680.73	280169.23
June	0.496953725	0.507214747	590783.15	597401.47
July	0.901634901	0.889241979	851802.19	843808.77
August	0.672019671	0.926209081	703700.53	867652.54
September	0.696886628	0.677485554	719739.70	707226.02
October	0.339551273	0.327644642	489258.64	481578.87
November	0.220917738	0.399080955	412740.09	527655.24
December	0.504816569	0.665440353	595854.64	699456.87

The actual EE consumption data for 2020 and 2021 and the EEEC data obtained from ANN were converted using Eq. 1, and the EEEC data in kWh are given in Table 3.

Table 4. Statistical data for 2018-2019 period.

Models	Hidden Layer	MAPE	MSE
Model 1	8 neurons	6.35115	0.01156
Model 2	9 neurons	5.50257	0.00616
Model 3	10 neurons	4.08579	0.00822
Model 4	11 neurons	3.42252	0.00355
Model 5	12 neurons	2.48655	0.00248

The number of neurons in the hidden layer was changed in ANN, and different models were used. The statistical data for MSE, MAPE and correlation values of each model are presented in Table 4. In addition, the EEEC data for 2020-2021 period and statistical data were compared for each model. The most accurate results for MAPE and MSE were obtained from Model 5.

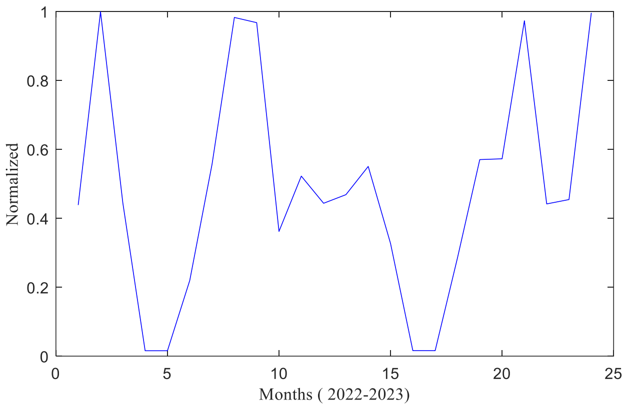

Figure 3. The normalized EEEC data for 2022-2023 period.

Monthly changes in the EEEC data obtained from ANN for 2022 and 2023 are shown in Fig. 3.

4. CONCLUSION

The present study performed the EEEC for prospective EE consumption based on the actual EE consumption data in KSU Avşar Campus from 2016 to 2021. To this aim, minimum-maximum normalization technique and different ANN models were used. To analyze and measure the performance of the proposed models, 48-month actual EE consumption data between 2016 and 2019 were used as a training dataset to perform the EEEC for 2020 and 2021. Later, the actual EE consumption data between 2018 and 2021 were used as a training dataset to perform the EEEC for 2022 and 2023.

EE consumption is a vital issue to be addressed in a national development plan. Given the continuous technological developments in the modern world, EE consumption is likely to increase day by day. Therefore, the EEEC data in the future must be performed accurately in order to avoid any potential problems resulting from an increasing energy demand for new institutional buildings and other technological developments. In this respect, it can be concluded that the present study makes an important contribution to a more effective budget planning at an institutional scale by drawing attention to accurate EEEC data for future periods.

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