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A novel artificial neural network model for forecasting electricity demand enhanced with population-weighted temperature mean and the unemployment rate

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Keywords
Monthly electricity demand
Balance point temperature
Unemployment Rate
Artificial neural network

ABSTRACT

Precise electricity demand forecasting has principal significance in the energy production planning of the developing countries. Especially during the last decade, numerous recent methods have been utilized to predict the forthcoming electricity demand in different time resolutions accurately. This contribution presents a novel approach, which improves the forecasting of Turkey's electricity demand in monthly time resolution. An artificial neural network model has been proposed with appropriate input features. Yearly-based gross demand shows approximately linear increment due to population increase and economic growth, while monthly-based gross demand indicates an oscillation due to the effect of seasonal temperature fluctuations. However, there is no clear linear relation between electricity demand and temperature; for the ideal case, it is the V-shaped curve around balance point temperature. Since temperature levels in each region of the country demonstrate a high variance even in the same time period, weighted average temperature point was calculated with respect to the population weights of the selected regions of Turkey. In order to fit a function for monthly oscillations, a linear function according to weighted average temperature point was created. Unemployment data was added to the training data set as an indicator of economic fluctuations. The mean absolute percentage errors of the model were calculated for training, validation, and testing as 3.77 %, 2.02 %, and 1.95 % respectively.

1. INTRODUCTION

In today's world, electricity consumption has an influential role in the growth of economies. Therefore, it has been one of the most significant energy types of end-users. As can be observed in many countries, the increase in electricity demand on the industrial side is considered to be a precursor to the development of the technology and the economy. Each country has its own particular electricity consumption behavior, which is directly affected by numerous factors such as population size, meteorological conditions, social, and economic parameters. Researchers have been broadly using various emerging techniques such as fuzzy logic, particle swarm optimization, ant colony optimization, genetic algorithm, artificial neural network, and support vector regression in the modeling of electricity demand. The studies have been shaped as the estimation of electricity demand with several distinct time resolutions in almost all developing countries.

This paper is organized as follows: Section 2 presents a brief historical background both in the world and in Turkey. In Section 3, how the data obtained, analyzed, and preprocessed before modeling is presented. Section 4 provides outcomes of presented model and gives a comparison with previous similar studies. Lastly, Section 5 summarizes the key results.

2. LITERATURE REVIEW

A survey of the studies reported in the literature on electricity demand prediction for the last decade reveals that researchers utilized many different techniques and data for various time resolutions. A study for India has been proposed, which can estimate the monthly peak demand with a multiplicative seasonal autoregressive integrated moving average (MSARIMA) method (Rallapalli and Ghosh, 2012). The time span was very narrow (April 2011 – July 2011) for the study and it

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cannot be applied to predict the demand for longer periods. Another model for the electricity demand prediction for India, the deep learning framework was presented in 2019 (Bedi and Toshniwal, 2019). In 2013, the least square - support vector machine (LS-SVM) method was shown to be more successful in predicting the hourly electricity load for Portugal over the 48-hour period when compared with the previous studies (Ferreira, et al., 2013). For the same year, a genetic algorithm (GA) model has been suggested in order to estimate the annual electricity demand of Thailand by using economic parameters such as gross domestic product (GDP) and total income as input features (Mostafavi, et al., 2013). Also, it was shown in the same year for Canada that neural-fuzzy logic network models could be employed to predict the demand for a 5-year period (Zahedi, et al., 2013). Then, hourly effects of weather variables were examined in an another study (Nick MacMackin, et al., 2019). Comprehensive studies were presented for Australia on a monthly estimation of electricity demand by using balance temperature point with utilizing multi-collinearity analyses (Ahmed, et al. 2012; Ahmed, et al. 2018). In 2015, electricity demand data with the 30-minute resolution had been trained with simply using time series as an input feature and had a 0.62% mean absolute percentage error (MAPE) (Vu, et al., 2017). In 2018, it was also shown that the atmospheric variables have effects on both monthly and annual electricity demands (Ahmed et al., 2018). Numerous studies have been published for Australia in 2019 (AL-Musaylh, et al. 2019; Singh, et al., 2019; Wu, et al., 2019; Xu et al., 2019; Yang, et al., 2019). A new model has been presented for the effects of temperature fluctuations for Korea on monthly electricity demand (Chang, et al., 2016). In another study for Korea, the monthly electricity demand has been estimated by the support vector regression SVR technique for the residential sector using social and weather variables for a 2-year range. The study has yielded exclusively training MAPE as 2.13% (Son and Kim, 2017). Also, a forecasting model was developed for institutional buildings in 2019 (Kim, et al., 2019). In 2016, a deep belief network, which has been one of the favorite methods in machine learning, was used to estimate the hourly electricity demand of Macedonia. To train the algorithm, the calendar and temperature information were used as model features. Estimated values generated a MAPE between 3.3% and 7.2% (Dedinec, et al., 2016). For Brazil, forecasting annual electricity demand was proposed using a fuzzy logic method with the help of GDP and population for 10-year period (Torrini, et al., 2016). Another study for Brazil, using similar input features, has demonstrated regional monthly electricity demand prediction with the help of spatial autoregressive integrated moving average (ARIMA) model (Cabral et al., 2017). The hourly and daily peak electricity demand in commercial buildings for Great Britain was estimated by using the triad demand predictive model with a 2.4% MAPE for training data only (Marmaras, et al., 2017). Also for Great Britain, time series analysis has been studied for electricity load forecasting in 2019 (Maldonado, et al., 2019). In 2015, self-adaptive particle swarm optimization (PSO), GA, and radial basis function (RBF) were used in a hybrid model, which presented to estimate annual electricity demand for China (Yu, et al., 2015). After three years, in 2018, electricity demands of two different regions in China were estimated by two different studies using similar Grey models without any economic parameters (Ding, et al., 2018; Wu, et al., 2018). In the same year, echo state network, which has been improved with differential evolution algorithm, was again presented to estimate monthly electricity demand for China (Wang, et al., 2018). A study on hourly peak demand of households in Denmark has been investigated with statistical data in 2017 (Andersen, et al., 2017). Other two studies using similar statistical techniques attempted to determine the factors affecting electricity demand for Israel (Damari and Kissinger, 2018) and Jordan (Al-Bajjali and Shamayleh, 2018). In South Africa, the demand-intensive hours were modeled with partially linear additive quantile regression between 18:00 and 20:00, for a 6-month time interval. The model was created by implementing hours of the day, date, and temperature as input features (Lebotsa, et al., 2018). In 2018, the hourly model of electricity demand in both commercial and residential areas of the USA was suggested to estimate for 250 hours by deep recurrent neural networks which is another recent popular method in machine learning. The model included all atmospheric events and calendar information (Rahman, et al., 2018). A summary of selected studies which fulfilled over the last decade can be seen in Table 1.

Electricity demand estimation of Turkey has also been studied by many researchers with different time resolutions and input parameters so far. The first studies were initiated at the beginning of the 2000s. In the study, they employed an exponential regression from 30-year (1970-2000) demand data to estimate the annual electricity demand for the next 50-year (2000-2050) time span (Yumurtaci and Asmaz, 2004).

Table 1. Summary of the electricity demand prediction studies in world.

Study	Methodology	Features	Forecast Span	MAPE validation	MAPE train
(Rallapalli and Ghosh, 2012)	MSARIMA	Time series	May-July 2011	0.93 – 0.94	1.60 – 2.05
(Ferreira et al., 2013)	LS-SVM	Time series	48 Hours	-	1.90 – 4.00
(Mostafavi et al., 2013)	Genetic programming and simulated annealing (GSA)	Time series, GDP, stock index, total revenue	2003 – 2009	0.50	2.30
(Vu, et al., 2015)	Multi-collinearity	Cooling degree days, heating degree days, number of rainy days in a month of interest, humidity percentage average	2006 – 2010	1.02	1.00 – 4.00
(Vu et al., 2017)	Autoregressive based time varying (ARTV) model	Time series	2015	-	0.62
(Son and Kim, 2017)	SVR and fuzzy-rough feature selection	20 variables are considered including 14 weather variables, 5 social variables, and monthly electricity consumption	2011 – 2012	-	2.13
(Dedinec et al., 2016)	Deep belief networks	Holiday flag, cheap tariff flag, hour of day, day of week, previous day's average load, load for the same hour of the previous day, temperature, load for the same hour - day combination of the previous week	2013 – 2014	-	3.30 – 7.20
(Torrini et al., 2016)	Fuzzy logic	Time series, GDP, population	2003 – 2013	-	0.93 – 2.38
(Cabral et al., 2017)	Spatial ARIMA model	Time series, average tariff in each region, number of residences served in each region, regional economic activity index adjusted seasonally	2013	1.85	-
(Marmaras et al., 2017)	Triad demand predictive model	Cloud base, cloud total amount, wind mean speed, rainfall, hourly global radiation, max gust, air temp deg., rh., hourly sun	2014 – 2015	-	2.40
(Yu et al., 2015)	PSO – GA – RBF	Population, GDP, energy intensity of industry	2014 – 2020	1.31	2.89
(Ding et al., 2018)	Modified grey prediction model	Time series	2012 – 2014	2.86 – 3.38	2.86 – 3.38
(Wu et al., 2018)	Multi-variable grey model	GDP, income, population, gross industrial output, fixed investment assets,	2013 – 2015	3.16	2.61
(Wang et al., 2018)	Echo state network	Time series	10/2008 – 05/2009	0.05	2.16
(Lebotsa et al., 2018)	Partially linear additive quantile regression	Temperature variables, calendar variables	January – June 2012	-	0.77 – 0.97
(Rahman et al., 2018)	Deep recurrent neural networks	Dry bulb, temperature, relative humidity, wind speed, solar irradiation, etc.	250 hours	-	5.46

In 2005, two different studies by the same group presented estimations for different time periods with the help of GA based on yearly resolutions (Ozturk and Ceylan, 2005; Ozturk, et al., 2005). The electricity generation and demand were compared between Turkey and European countries in 2006 (Tunç, et al., 2006). Annual electricity demand and production were modeled with two different methods based on the same learning set in 2007. The Grey prediction model was studied in the first method, and simply time series was chosen as the input feature of the model (Akay and Atak, 2007). In the second study, the annual electricity demand was modeled by a quadratic function, and its parameters were found with the help of ant colony optimization (ACO) (Duran Toksari, 2007). In 2009, economic parameters were included in the artificial neural network (ANN) model, and electricity demands between 2001 and 2006 were estimated with a 0.51 root mean square error (RMSE) per TWh (Kavaklioglu, et al., 2009). The support vector machine (SVM) method was employed to estimate for the same time period by using the same data in 2011 (Kavaklioglu, 2011). A fuzzy logic model was also applied to estimate the total electricity generation in 2010 with the help of total domestic product as an input feature (Kucukali and Baris, 2010). Another study in 2011 established an electricity demand model of residential buildings and exhibited the factors which are effective on the model (Dilaver and Hunt, 2011). By the year of 2012, both training and validation metrics have been delivered in research studies which performed to predict Turkey's electricity demand. Before 2012, studies only presented either the training or the validation metrics. In 2012, monthly electricity demand was investigated for the first time for Turkey. SVR algorithm was utilized for the model, and the MAPEs of both training and validation data sets were calculated as 11.00% and 3.30% respectively (Oğcu, et al., 2012). In another study, a quadratic second order function was fitted with the help of PSO, and the error was decreased down to 3.99% (Kiran, et al., 2012). In 2014, three different studies with three characteristic methods were presented. The first one has been demonstrated that the electricity demand in both industrial and residential buildings could be modeled by using merely time-series (Arisoy and Ozturk, 2014). In the second study, the optimized Grey model was presented to estimate input features for the singular value decomposition (SVD) method from 1970 to 2010 (Kavaklioglu, 2014). In 2015, a model was proposed to estimate the future independent factors using seasonal ARIMA method and non-linear autoregressive ANN method (Tutun, et al., 2015). Hourly electricity demand was estimated with a 1.85% MAPE by using an ANN model (Çevik and Çunkaş, 2015). In the same year, ANN and LS-SVM were compared on annual electricity demand, and LS-SVM has demonstrated better estimation results. (Kaytez, et al., 2015). Similarly, ANN was also compared with multiple linear regression (MLR) model on the annual electricity demand, and it was concluded that the ANN model successfully predicted the electricity energy demand with extreme accuracy, and the forecasts were superior to the official forecasts done by Ministry of Energy and Natural Resources of Turkey. On the other hand, the MLR model was not successful enough to predict the demand within an acceptable accuracy range (Günay, 2016). In 2016, ACO and iterative local search algorithms were used to fit a quadratic function to estimate electricity demand (Toksari, 2016). In 2017, three different studies were performed to estimate daily, monthly, and annual electricity demand. For the estimation of daily electricity demand, sinusoidal oscillations were modeled with temperature data on a linear model that took into account these fluctuations (Yukseltan, et al., 2017). For the estimation of the monthly electricity demand, an ANN with feedback was trained, and MAPE decreased down to 2.28% for the test set (Hamzaçebi, et al., 2017). The yearly prediction demand was linearly modeled with parameters of GDP, population, import and export. The parameter weights of the model were optimized by the help of the PSO algorithm. The model yielded a 2.52% MAPE for the years from 2004 to 2013 (Gulcu and Kodaz, 2017). In 2018, daily electricity demand was estimated with multivariable adaptive splines, and the model has exhibited a 4.00% MAPE on the test set (Nalcaci, et al., 2018). A summary view of selected studies which fulfilled over the last two decades for Turkey can be seen in Table 2.

3. METHOD

In this study, ANN is chosen as a forecasting tool since it can intrinsically model the non-linear behavior in the data. Only time series, temperature data and the unemployment rate were used as input features. In order to keep the model simple, the other economic parameters like GDP, import and export were excluded. Section 3.1 clarifies how population-weighted monthly average temperature point is calculated for Turkey. This function is employed as an additional input feature of the proposed neural network.

Table 2. Summary of the electricity demand prediction studies in Turkey

Study	Methodology	Features	Forecast Span	MAPE validation	MAPE train
(Ozturk et al., 2005)	GA	Time series, gross national product, population, import and export	1996 – 2001	2.29	1.42
(Ozturk and Ceylan, 2005)	GA	Time series, gross national product population,, import and export	1997 – 2003	7.30-16.05	-
(Akay and Atak, 2007)	Grey prediction	Time series	-	3.43-4.36	-
(Duran Toksari, 2007)	ACO	Time series, GDP, import, export and population	-	1.00-3.00	-
(Kavaklioglu et al., 2009)	ANN	Time series, gross national product, population, import and export	2001 – 2006	-	0.51 RMSE per TWh
(Kavaklioglu, 2011)	SVR	Time series, gross national product, population, import and export	2001 – 2006	-	0.76 RMSE per TWh
(Kucukali and Baris, 2010)	Fuzzy logic	GDP	-	4.16	-
(Oğcu et al., 2012)	SVR	Time series	2010 – 2011	11.00	3.30
(Hamzacebi and Es, 2014)	Optimized grey model	Time series	2006 – 2010	-	3.28
(Kavaklioglu, 2014)	SVD	Time series, gross national product, population, import and export	1970 – 2010	-	-
(Tutun et al., 2015)	Ridge-based adaptive evolutionary	Time series, imports, exports, gross generation and transmitted energy	2006 – 2010	0.18	1.60
(Çevik & Çunkaş, 2015)	Adaptive neuro-fuzzy inference system	Load, temperature, season	2012	-	1.85
(Kaytez et al., 2015)	ANN and LS-SVM	Installed capacity, gross electricity generation, population	2010 – 2011	0.88	1.00
(Günay, 2016)	ANN	Population, gross national product, inflation, unemployment, average summer temperature, average winter temperature	2007 – 2013	-	2.52
(Toksari, 2016)	ACO	Time series, gross national product, population, import and export	2004 – 2013	Lin.= 1.15 Qua.=2.16	-
(Yukseltan et al., 2017)	Linear model	Time series, religious holidays	2014	-	2.86
(Hamzaçebi et al., 2017)	ANN	Time series	2014	1.97	2.28
(Gulcu and Kodaz, 2017)	PSO	GDP, population, import, export	2014 – 2030	2.52	-
(Nalcaci et al., 2018)	Multivariate adaptive regression splines	Lags of electricity demand, holidays, temperature date, relative humidity, wind speed	2013 – 2015	3.60	4.00

3.1. Preprocessing

Seven big provinces from each geographical region were selected to represent Turkey. These cities were picked as Istanbul, Ankara, Izmir, Adana, Diyarbakır, Trabzon, and Erzurum. These cities and geographical regions are shown in Figure 1. Monthly mean values of temperature recordings for each region were used as an additional input data from January 2000 up to November 2019 (MGM, 2020).

Figure 1. Selected cities on the geographical region map

The weather data was requested from the Turkish Meteorological Data Information Sales and Presentation System. The most reliable and some of the oldest meteorological stations were preferred in order to have complete temperature information for each city.

Residential populations were used for the year of interest, and the data was downloaded from the Turkish Statistical Institute website (TUIK, 2020). For the year of 2019, the total population of the cities, which is 37.39% of the overall population of Turkey and their population weights were calculated among themselves, can be seen in Table 3.

Table 3. Populations of selected cities and their weights for the year of 2019

Province	Population	Weight
Istanbul	15,029,231	0.498
Ankara	5,445,026	0.180
Izmir	4,279,677	0.142
Adana	2,216,475	0.073
Diyarbakır	1,699,901	0.056
Trabzon	786,326	0.026
Erzurum	760,476	0.025

The electricity demand data was collected from Turkish Electricity Transmission Company (TEIAS) (TEİAŞ, 2020). The monthly gross electricity demand was selected as an input from January 2000 up to November 2019. It can be easily seen in Figure 2 that entire electricity demand data even with short-term variations may fit almost linearly with a reasonable R^2 value of 0.935.

The unemployment rate data was collected from Turkish Statistical Institute (TUIK, 2020). The data was used as an economic indicator of Turkey. It can be clearly seen from Figure 2 that unemployment rate and electricity demand have an inverse correlation.

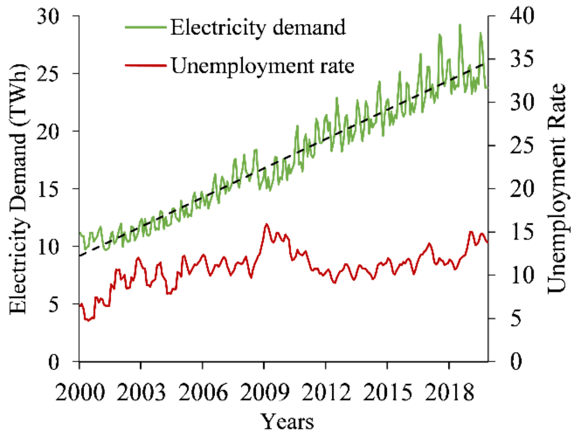

Figure 2. Electricity demand and unemployment rate of Turkey

To clearly observe the oscillations on the monthly electricity demand; the average demands for the same month of all years were calculated (see Figure 3 (right)). Monthly variation of electricity energy demand was observed to be highly correlated with the calculated average temperatures. The square difference of the monthly temperature averages around a fixed BPT is extremely similar to the monthly energy demand (ED) oscillations, as shown in Figure 3 (left) Therefore, it can be eventually determined that monthly electricity demand shows a superposition of a linear increase over the years and intensifying oscillations around the monthly temperature averages. In the light of these observations, a function prototype was proposed as in Equation 1.

$$ED(y,m,T_m) = a\left[12\left(y-y_{offset}\right)+m\right] + b\left[12\left(y-y_{offset}\right)+m\right]\left(T_m-T_b\right)^2 + D_{offset} \quad (1)$$

The constants were calculated with the help of the “Levenberg-Marquardt” algorithm. They were obtained as demand increase slope a = 6.516e-9, year offset y_{offset} = 1994.937, demand oscillation magnitude b = 1.056e-11, balance point temperature T_b = 15.227, constant electricity consumption D_{offset} = 0.005. Where, the coefficient a represents the slope of linear electricity energy demand increase and the coefficient b represents the amplitude of oscillations on electricity demand over BPT.

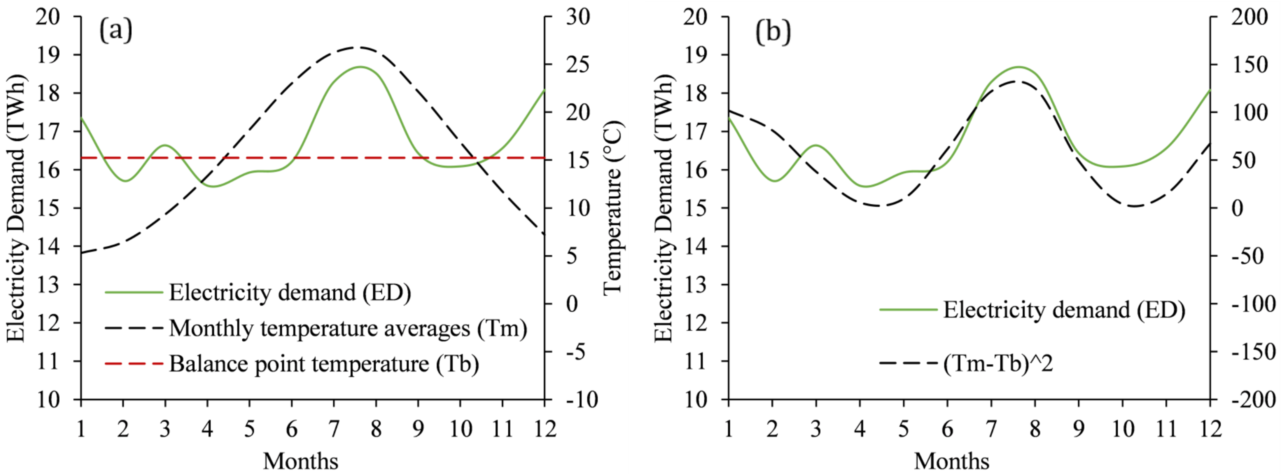

Figure 3. (a) Determining balance point temperature by using averages of temperature variations. (b) Catching similarity between electricity demand fluctuations across months between squared differences of average temperatures with BPT

Electricity energy demand recordings are shared with the function whose constants are calculated. Here D_{offset} shows the constant electricity consumption in PWh, which is not related to oscillations. y_{offset} is the year in which oscillations started. T_m is monthly temperature average and used as an input attribute as $(T_m - T_b)^2$ into the proposed artificial neural network model. This value has helped us to find linear and non-linear relations in the model to predict the temperature-dependent monthly oscillations.

3.2. Multi-layer perceptron networks

An ANN model plainly defines a potential solution space. Neural Network can be defined as seeking for useful mapping of input features to output target within a predefined possibility space of solutions by the help of back-propagation. By picking a model out, one constrains the space of potentiality to specific limits. The field of ANN is often just called multi-layer perceptron since it is the most useful kind of neural network. A multilayer perceptron (MLP) must contain one or more hidden layers besides one input and one output layers. MLP intrinsically possess an ability to learn non-linear functions. Consequently, they own the power to find out the representation in the training data and how to effectively relate it to the output targets that wanted to predict. In this sense, the predictive capability of neural networks comes from the structure of multi-layer. However, the layer could simply learn the linear mapping of the input features without a non-linear activation function since a sequential pile of linear layers would still carry out a linear function. Therefore, contributing more layers would not broaden the potential solution space. In order to have a much extensive potential solution that would profit from multiple mapping, a non-linear activation function is essential between layers.

3.3. Proposed MLP network model

The suggested model consists of an input layer with 15 neurons (1 input for year, 12 inputs for months, 1 input for $(T_m - T_b)^2$, and last input for unemployment rate), 2 hidden layers, and an output layer with one neuron which gives the prediction of energy demand. All neurons are fully connected to the previous and next layers. A model that has less than two hidden layers could not sufficiently learn the pattern in the training data. Therefore, it could not implement a good representation of the input features. Whereas, adding more hidden layers would cause to determine more complicated representations which makes the model computationally expensive and might also contribute to learn undesirable patterns that would improve the performance of the training but not both of the validation and test data sets. A model that does well on the training set is not needfully a model that will performs well on another data set it has never encountered earlier. The fundamental problem in the neural network is the balance between optimization and generalization. Optimization is adjusting a model so that having the most beneficial performance possible on the training data. On the other hand, generalization is indication of how well the model does on the validation data it has never met before. The principal aim is to have good generalization based on training data. Regrettably, there is no known quick process to find the proper number of layers or the correct number of neurons for each layer. In order to determine an appropriate model size in the study, different architectures have been evaluated on training and validation data. Nevertheless, test data has never been used at this stage. Additionally, the training data set has been shuffled to mitigate overfitting. Year and $(T_m - T_b)^2$ values are entered in the model after scaling since feeding relatively large values as input features could incite large gradient modification that will preclude the network from converging. However, the unemployment rate is fed into the model without scaling because its values are already defined as small numbers. Month values were entered as one-hot encoded value. Therefore, exclusively month of interest is entered as 1 and others are entered as 0. The structure of the proposed model can be seen in Figure 4.

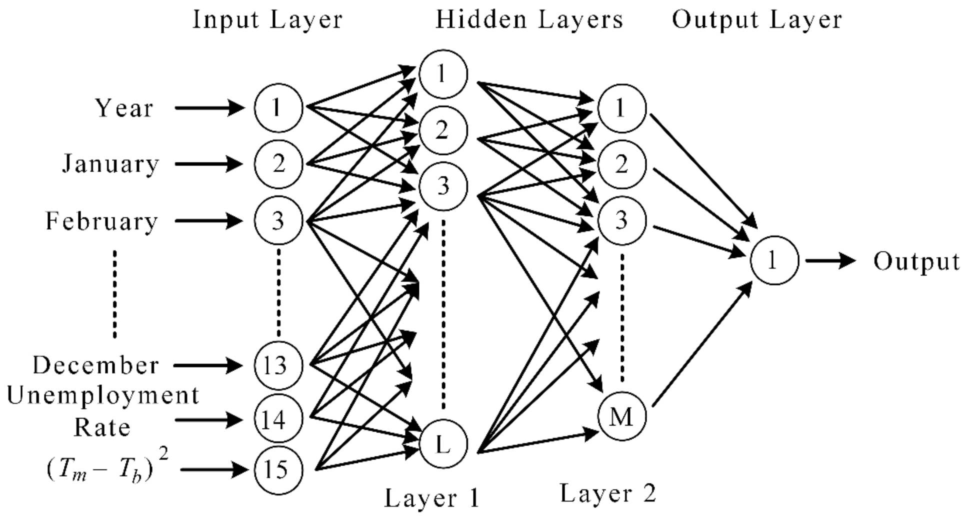

Figure 4. Proposed MLP network scheme

3.4. Evaluation metrics

The performance of the proposed MLP network scheme evaluated using MAPE according to the output of each month with the help of Equation 2. MAPE metric has been chosen as an error metric of the model. The model was created with the help of Sci-kit Learn MLP regressor, and the Limited-memory Broyden Fletcher Goldfarb Shanno algorithm (LBFGS) was chosen as optimizer of the model. As a default value in the MLP regressor, mean square error (MSE) is used as loss function of the back-propagation process.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{Y_i}\right| . 100 \quad (2)$$

Where n is the number of samples, e_i is the error, and Y_i is the real value of the i^{th} element.

4. RESULTS

The hyper-parameter space has been selected as wide as possible in order not to miss any potential solution. In the training phase, 500 best results were chosen as likely solutions candidates. Nevertheless, most of 500 candidates were trained so well with training data so that it has actually memorized the data. Therefore, they have over-fitted the training data; however, fitted very poorly the validation data. In the validation phase, validation data was used to optimize the model parameters. In other words, the ultimate model was selected among these likely solutions by using only validation data. The selected hyper-parameters can be seen in Table 4. It is fundamentally important that test data has not been used during any phase of the training or hyper-parameter selection.

Table 4. Selected hyper-parameter set after validation phase

Name	Values
Activation functions	Rectified linear units (RELU)
Alpha	1e-6
Number of hidden layers	2
Hidden layer sizes	32, 10
Max. iteration count	5000
Solver function	LBGFS
Random seed	870899622

The graphical representations of training can be seen in Figure 5. Actual measurements are given in green, predicted values are shown in red and absolute percentage error (APE) rates for each month dedicated at the bottom of each graph as percentage error with blue bars. The demand data from 2000 up to end of 2017 was chosen as a training set. Neither validation nor test data were used in the training phase.

In order to demonstrate the robustness of the model, a comparison of actual demands and prediction values, which obtained from the proposed model have been made. The real and predicted demand values of validation and test set can be seen in Table 5. The validation data contains all 12 months of 2018, and the test data comprises of 11 months of 2019.

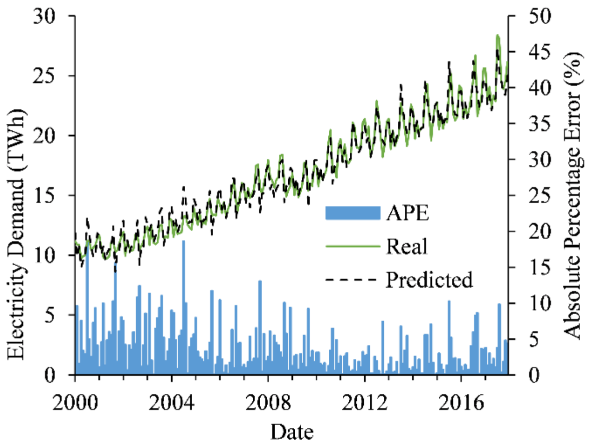

Figure 5. MLP training results with APE

By the help of MAPE metric, the proposed study has also been compared with previous works, which were studied on monthly energy demand for Turkey as can be seen in Table 6. Both the validation and test metrics of the suggested model have been measured more accurately than the metrics of former SVR (Oğcu et al., 2012) and seasonal ANN (Hamzaçebi et al., 2017) models. Only seasonal ANN model performs a better training set over the proposed model. However, their MAPE values of validation and test sets give higher values. In this case, the model shows a little overfitting. On the other hand, the suggested model gives superior results for both validation and test sets without any observable overfitting.

Table 5. Results and comparisons for each month of validation and test data sets

	Date	Real Electricity Demand (TWh)	Predicted Value (TWh)	APE
Validation Set	01/18	26.21	25.01	4.59
	02/18	23.23	23.32	0.36
	03/18	24.73	24.28	1.82
	04/18	23.59	23.04	2.32
	05/18	23.97	23.86	0.44
	06/18	23.86	24.06	0.85
	07/18	29.22	28.57	2.22
	08/18	27.56	26.28	4.63
	09/18	25.05	25.71	2.62
	10/18	23.38	24.16	3.37
	11/18	23.85	23.91	0.24
	12/18	25.48	25.69	0.82
			Validation MAPE :	**2.02**
Test Set	01/19	25.74	25.46	1.09
	02/19	23.20	23.83	2.75
	03/19	24.63	24.74	0.45
	04/19	23.42	23.48	0.24
	05/19	24.60	24.22	1.54
	06/19	24.04	24.68	2.65
	07/19	28.52	28.54	0.09
	08/19	27.51	26.47	3.81
	09/19	25.12	25.41	1.15
	10/19	23.74	24.76	4.31
	11/19	23.74	24.56	3.43
			Test MAPE :	**1.95**

Table 6. Comparison with previous models for Turkey

Study	MAPE		
	Train (Years)	Validation (Years)	Test (Years)
(Hamzaçebi et al., 2017)	**1.97** (2002 – 2012)	2.31 (2013)	2.28 (2014)
(Oğcu et al., 2012)	11.00 (1970 – 2009)	3.30 (2010 – 2011)	-
Proposed study	3.77 (2000 – 2017)	**2.02** (2018)	**1.95** (2019)

5. CONCLUSION

A robust MLP model has been suggested to forecast the monthly electricity demand of Turkey. 500 potential models have been chosen based on training data, then the hyper-parameters of the model were decided to choose the best model based on validationdata. The sucggested MLP model accomplishes exceptional consistency with the data sets of training, validation, and test. Although validation and test data sets were not utilized during the training phase of the model, it achieves relatively low errors for not only training data set but also both validation and test data sets.

Moreover, the studied model is also considerably successful when it is compared with previous models to make a forecast of the electricity demand of Turkey. The substantial prediction of electricity demands with a relatively simple model is the distinctive advantage of the model. As the proposed model incisively estimates the demand for approximately 2 years, governments and decision-makers who decide how much electric power installation will be required, can reliably utilize the model to confirm their ultimate determination with no need any profound mathematics and statistical background.

Proposed model decreases MAPE as low as 3.77%, 2.02%, and 1.95% on training, validation, and test data sets respectively for monthly electricity demand estimations without employing any economic parameters like the gross national product, import or export as an input feature except unemployment rate. The maximum value of the MAPE was observed for the time between 2009 and 2011 in training data set due to the fact of the financial crisis during this period.

As a future research, error rates of electricity demand prediction can also be decreased by applying the recurrent neural network models which are very good in time series inputs.

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DATA AVAILABILITY

The electricity, population, and temperature dataset are hosted on Github (Cömert, 2020) with BPT calculation function script, which was written for Octave software.

Author contributions

Mustafa Cömert: Conceptualization, Visualization, Methodology, Software, Algorithmic Model, Writing-Original Draft Preparation. **Ali Yıldız:** Methodology, Investigation, Algorithmic Model, Model Validation and Test, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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