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GMDH-type neural network-based monthly electricity demand forecasting of Turkey

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ABSTRACT

In this study, it was intended to develop an accurate forecasting model for the monthly electricity demand of Turkey in the medium-term. For this purpose, the Group Method of Data Handling (GMDH)-type Neural Network (NN) approach was utilized to structure a nonlinear time-series based forecasting model. A large dataset containing monthly electricity demand was considered for the period of 2003-2018. The developed model was tested in the period of 2019/01-2019/11 in order to specify the generalization ability. The test results showed that the developed model was very close to actual values. The obtained test performances were 2.10 % for mean absolute percentage error (MAPE), 2.36 % for root mean square percentage error (RMSPE) and 0.869 for coefficient of determination (R^2). In addition, results of the developed GMDH-type NN model were compared to the forecasting results of a literature study. The comparison revealed that GMDH-type NN was a better approach for forecasting the monthly electricity demand for Turkey. Finally, the developed model was utilized to forecast monthly electricity demand in the period of 2019/12-2020/12.

1. Introduction

Currently, the technical, economic and social development of any nation state in the world depends largely on the utilization of electrical energy [1]. Electricity is required for almost all types of human actions such as manufacturing, agriculture, housing, heating, lighting, and transportation. Moreover, the electricity consumption per capita that is a direct measure of the standard of living is used as a descriptive indicator to determine the development stage of countries [2]. Furthermore, based on primarily growing population and desired welfare and living conditions, the use of electricity increases from year to year [3]. From this point of view, future electricity demand in a country should be accurately forecasted and carefully planned in order to maintain the demand-supply balance by making the required investments on time [4].

In this aspect, Turkey is located at a strategic geographical location connecting from Middle-East and Asia regions, where conventional energy sources are abundant, to Europe where energy consumption is significantly high [5]. However, Turkey has inadequate oil and natural gas reserves. They are 44.3 million tons for oil and 6.2 million m^3 for natural gas. Hydroelectric, low-quality lignite coal, and wind are the main domestic energy resources of Turkey. Therefore, it is extremely dependent on foreign fossil fuels to meet the growing electricity demand [5]. Electricity demand increases day by day in Turkey regarding economic and population growth [6,7]. The country's total electricity generation increased from 23.275 TWh in 1980 to 304.800 TWh in 2018. At the same time, with the technological progress (smart grids), electricity demand forecasting becomes more critical for grid operators, market participants, regulators, and ministers in terms of planning and operational decisions. It is obvious that precise electricity demand forecasting is curicial for the protecting the finite resources, but it is still a problematic issue because of the stochastic and ambiguous characteristics [8].

In the related literature, a number of studies concerning electricity demand forecasting have been carried out based

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on different methods over the years. Generally, load/demand forecasting methods can be separated to two leading categories: i) Conventional Statistical, and ii) Artificial Intelligence (AI) methods [8,9]. The conventional methods contain multiple linear regression, similar-day techniques, exponential smoothing models, semi-parametric additive models and time series modeling including seasonal autoregressive integrated moving average (SARIMA), autoregressive integrated moving average (ARIMA), autoregressive moving average (ARMA), etc. [10-16]. On the other hand, the artificial intelligent methods consist of artificial neural networks (ANNs), fuzzy logic, genetic algorithm, grey prediction, adaptive neuro fuzzy system, expert systems, support vector machines, and hybrid methods [2,3,17-22]. Not every method is appropriate for all forecasting problems because there is not an agreement on the best method. However, contemporary studies have shown the power of ANNs in forecasting electricity demand [20, 23-26]. However, the challenging point in designing ANNs is the choice of the finest network architecture that can provide the best results. This is a great task since the architecture of the network includes many important points, for example, the neuron number in different layers, layer number, and number of inputs and outputs [24]. When the Group Method of Data Handling (GMDH) is applied in the building of ANNs, the main problems mentioned above can be overcome because it has the ability to generate the network automatically [27]. In this study, the GMDH approach was used as one of the Neural Networks (NNs), which was named GMDH-type NN, and it is explained in detail in the next section.

The demand forecasting can be grouped namely with regard to the time horizon. It can be typically divided into three periods. First group is long term specified from a year to a decade. Second group is medium-term quantified from a week to a year. Third group is short-term measured from 1 h to 1 week. Acquiring important knowledge for the cost-effective and safe operation of the power generation systems is aimed at short-term forecasting. The long-term forecasting is applied for investment planning and decisions. Instead, the medium-term forecasting contributes on meeting load conditions, fuel purchasing plans, outage & maintenance arrangement, organization of load dispatch and bill payment, cost-effective operation of the electricity generation system, and improved agreement debates in electricity trading [8,9,28]. In this study, medium-term forecasting is considered with placing special emphasis on the monthly electricity demand of Turkey. It is seen in the associated literature that although a number of studies related to the estimating Turkey's electricity demand, most of these studies have been conducted to forecast annual demand for long term [2,4,5,7,10,11,18,19,22]. It is clear that there is a lack of studies regarding the medium-term electricity demand of Turkey. Only, a few studies are related to the monthly electricity demand forecast even though it has significant roles in the planning and marketing of electricity generation systems. For instance, İlseven and Göl [8] applied multivariate adaptive regression splines technique to forecast monthly electricity demand of Turkey. They indicated that their model achieved successful results in validation step by testing error and their model showed steady forecasting performance. They concluded their study by forecasting monthly electricity demand for the years of 2017-2019. Hamzacebi et al. [26] proposed four different seasonal artificial neural network models and chose the best one to predict Turkey's monthly electricity demand. They finalized their study by implementing the best ANN structure to estimate monthly electricity demand for the years from 2015 to 2018.

In this study, the medium-term based Turkey's electricity demand was forecasted by the GMDH-type NN approach. The core novelty of this study is to implement the first time the GMDH-type NN to Turkey's monthly electricity demand forecasting. For this purpose, the GMDH-type NN model was developed using the monthly dataset of the years 2003-2018 and tested in the period of 2019/01-2019/11 to reach highly accurate predictions. The graphical and statistical analyses were used to show model success and consistency. Besides the forecasting outcomes of a related literature study were compared with the results of the suggested GMDH-type NN model. Lastly, the developed model was applied in the period of 2019/12-2020/12 to estimate monthly electricity demand.

2. GMDH-type Neural Network

GMDH can be considered as a self-organizing ANN which was developed to model multi-variable and non-linear complex systems based on the relationships between inputs and outputs by Alexey G. Ivakhnenko in 1971 [29]. GMDH-type NN, fundamentally a feed-forward and multi-layered neural network, has been implemented to several engineering problems [30- 33].

The training procedure of the GMDH-type Neural Network is based on evolutionary mechanism, unlike the conventional neural network [34]. The GMDH algorithm is represented by a series of neurons in which different pairs of neurons are coupled via a quadratic polynomial and generate new neurons in the subsequent layer. The key input variables, number of layers, number of active neurons, and neurons in hidden layers are automatically constructed by the self-organization of the neural network [33]. Employing an iterative mechanism, the model architecture is adapted to produce the maximum accuracy without any overfitting in data prediction. In other words, to optimize the network, the links among neurons of the related network does not stay constant, on the contrary, they are chosen during the training process [35,36]. Fig.1 illustrates the general structure and configuration process of GMDH-type NN.

This network identifies the approximate function of $\hat{f}$ through the predicted output of $\hat{y}$ with the minimum error. Guadratic polynomials resulted from all neurons for a set of multi inputs $X=(x_{i1},x_{i2},x_{i3}.....x_{in})$ are combined and the predicted output is compared to the actual single output of y [33]. Therefore, the actual results for the experimentally measured *M* data consisting of *n* inputs and single-output can be stated as following [31]:

$$y_i = f(x_{i1},x_{i2},x_{i3},\ldots,x_{in}) \quad (i=1,2,3,...,M) \tag{1}$$

To estimate the value of $\hat{y}$ for the input vector of X, a GMDH-type NN is developed as below:

$$\hat{y}_i = \hat{f}(x_{i1},x_{i2},x_{i3},...,x_{in}) \quad (i=1,2,3,...,M) \tag{2}$$

The GMDH-type NN have to minimize the squared error between the estimated and the actual values given as following:

$$\sum_{i=1}^{M}(\hat{y}_i - y_i)^2 \rightarrow min \tag{3}$$

The mathematical description between the output and input variables is formulated with utilizing a complex discrete procedure of the functional series recognized as the Kolmogorov–Gabor polynomial [29,32], as given in Eq.(4):

$$\begin{aligned} y &= a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}x_i x_j \\ &+ \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk}x_i x_j x_k + ... \end{aligned} \tag{4}$$

Where *n* is the number of input variables, $(x_1,x_2,...,x_n)$ are the input parameters, and $(a_0,a_1,...,a_n)$ are the coefficients. The quadratic and bivariate structure of this polynomial expression is employed usually by total algebraic arrangement [36] given as following:

$$\begin{aligned} \hat{y}_i &= G(x_i,x_j) = a_o + a_1x_i + a_2x_j \\ &+ a_3x_i^2 + a_4x_j^2 + a_5x_ix_j \end{aligned} \tag{5}$$

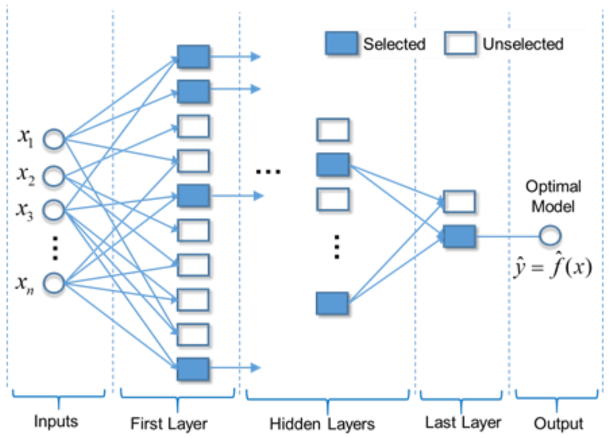

Figure 1. Configuration process of GMDH-type neural network

In order to produce the overall mathematical relationship of input and output variables presented in Eq.(4), such partial quadratic structure is implemented in a opposite route throughout a network of joint neurons [33]. To determine the unknown coefficients of a_i in Eq.(5), the regression technique is performed. Thus, for each pair of input variables (x_i and x_j), the minimum difference between the estimated values ($\hat{y}$) and the actual output (*y*) is provided [31]. By means of Eq.(5), a group of polynomials is established. The least squares technique is implemented to determine the unidentified coefficients of the mentioned polynomials. For the constants for each quadratic function G_i, the coefficients are acquired to minimize the total neuron error in order to achieve optimal fit of the inputs, as follows:

$$E = \frac{\sum_{i=1}^{M}(y_i - G_i)^2}{M} \rightarrow min \tag{6}$$

Taken into consideration the GMDH procedure, two independent possibility parameters are made available by the whole set of *n* chosen input parameters. Similarly, the stated technique, $n(n-1)/2$ neurons are going to set through first hidden layer computed from $\{(y_i,x_{ip},x_{iq});(i=1,2,...,M)\}$ on behalf of different $p,q \in \{1,2,...,n\}$. Hence, M data trebles $\{(y_i,x_{ip},x_{iq});(i=1,2,...,M)\}$ are determined through the $p,q \in \{1,2,...,n\}$ from the observation as follows [31,35]:

$$\begin{bmatrix} x_{1p} & x_{1q} & y_1 \\ x_{2p} & x_{2q} & y_2 \\ x_{3p} & x_{3q} & y_3 \end{bmatrix} \tag{7}$$

The second-order form of the expressed function (Eq. 5) is utilized for each M triple row. These equations expressed in the following matrix form:

$$Aa = Y \tag{8}$$

$$a = \{a_0,a_1,a_2,a_3,a_4,a_5\} \tag{9}$$

$$Y = \{y_1,y_2,y_3,...,y_M\}^T \tag{10}$$

where a denotes the vector of unknown coefficients presented in Eq.(5) and Y refers to the outputs' vector. Thus, the formulated correlation is given as following:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}^2 & x_{1q}^2 & x_{1p}x_{1q} \\ 1 & x_{2p} & x_{2q} & x_{2p}^2 & x_{2q}^2 & x_{2p}x_{2q} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}^2 & x_{Mq}^2 & x_{Mp}x_{Mq} \end{bmatrix} \tag{11}$$

With examining the multiple-regression outcome, the least square technique is completed by Eq. (12):

$$a = (A^TA)^{-1}A^T \tag{12}$$

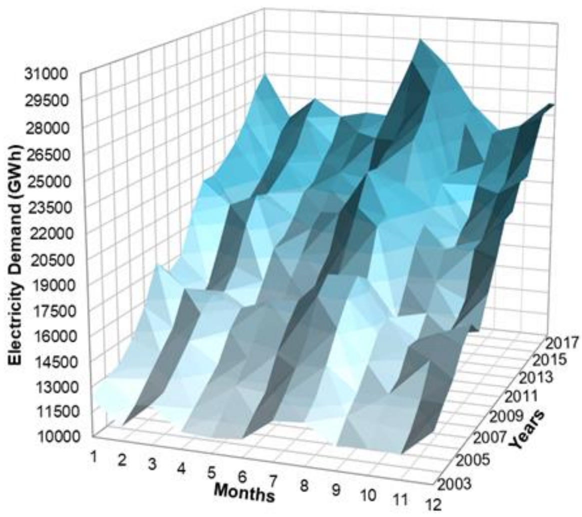

Figure 2. Monthly gross electricity demand of Turkey between 2003 and 2018

The most precise values of the coefficients given in Eq.(5) for M triple datasets of inputs are determined by the Eq.(12). In this architecture, the training algorithm is initiated by the input layer which is only a starting layer and does not comprise any process. In the first layer, based on all probable arrangements of input variables, the neuron candidates are produced. Then, the coefficients of Eq.(5) are determined for each respective neuron. By means of both the determined coefficients and input variables for each neuron, the desired output is estimated. Some neurons with well prediction ability are chosen according to external criteria and fed forward to train the next layer. The neurons which do not cover the considered condition are disregarded from the structure of the network. The outcomes achieved with the chosen neurons turn into the inputs for the subsequent layer. This procedure carry on up to the final layer. In the final layer, only one neuron is chosen. The achieved result in the final layer is the estimated values.

3. Model Development

The main aim of the study is to estimate Turkey's monthly electricity demand by employing GMDH-type NN method. Therefore, in this division, methodical steps of model development comprising of data collection, model configuration, and determination of performance criteria are given to achieve a successful forecasting result. Brief information about these steps is introduced in the subsequent subsections

3.1 Data Collection

Monthly gross electricity demand data for Turkey was obtained from the Turkish Electricity Transmission Company [37]. The data cover a period of monthly electricity demand values from January 2003 to November 2019. The data up to the year of 2019 are given as graphically in the Fig.2. The electricity demand has been increasing over the years in Turkey. In the given period, electricity demand rose by about 6% annually. There are seasonal behavior and monthly trend in data. Seasonally, whereas the demand for electricity is high in winter and summer months and reaches a peak usually in July or August, and it is low in autumn and spring months and gets the lowest point generally in February or October. This kind of seasonality behavior explains the connection between the climate situations in different seasons and electricity demand.

The collected data were analyzed, interpreted and apportioned into the model with a basic routine. The data were separated into two dataset. They are named as model development and testing parts. The model development dataset included monthly data in the period of 2003/01 – 2018/12, while the testing set comprised the period of 2019/01- 2019/11. The model development dataset was used for the configuration of the GMDH-type NN model. On the other hand, the testing set was used to measure the capability of generalization of the developed model.

3.2 Model Setup

The model was developed using the software package named as GMDH Shell 3.8.9. In this section, the procedures and steps for developing a forecast model by using GMDH Shell are given systematically. The monthly electricity demand data including time-stamps information were compiled using the MS Excel spreadsheet. The excel file was introduced to the modeling media in CSV/XLS/XLSX structure. Model development and testing datasets were adjusted as defined in Subsection 3.1. The dataset was preprocessed to transform data in accordance with configured modeling conditions in the module of data explorer. The input and target (output) variables were specified by several transformations such as elementary functions (e.g. sin, cos, cube), time series (e.g. lags, weighting, moving average), date/time extracting information from timestamps (e.g. month, year), weighted instances setting custom weights for target instances and so on.

Then, the solver module was used to produce predictive models for the target variable. The first thing to do was reorder observation, which was utilized to accomplish unvarying statistical features of training and testing samples as well as to make these parts similarly explanatory. The pseudorandom option was selected for the reorder observation process. The k-fold method was used to model the validation strategy and sorting out. The k-fold validation separates dataset into k sections, trains a model k times utilizing k-1 sections, and measures model performance each time utilizing a fresh left behind portion. As a final point, for comparing model, residuals acquired from entire testing parts were included and utilized.

Table 1. Main properties of the developed model in GMDH solver section

Properties	Selected option
Reorder observation	Pseudo-random
Validation strategy	k-fold
Validation criterion	RMSE
Variable ranking	No
Core algorithm	GMDH neural network
Neuron function	Polynomial and quadric polynomial

The root mean square error (RMSE) was utilized for a model selection measure, which selected the models with the lowest RMSE calculated for the testing sample. Polynomial neural networks of GMDH-type were used as the statistical learning algorithm. A different number of input variables can be permitted for a neuron. Using two inputs for any neuron is significantly effective way. Apart from that, the calculation charge can be excessively difficult. A polynomial and quadratic polynomial can be preferred as an interior function for neurons. To enhance the general estimation ability of the model, each neuron can eliminate some of the function parts. Specifying the maximum number of layers controls the higher boundary of the NN layers generated through the GMDH algorithm. The number of neurons that will be included to the set of inputs in each subsequent layer is determined by the initial layer width. The selected main properties of the model are given in Table 1. The other specified properties are presented in the Results and Discussion section.

3.3 Performance Criteria

It is expected from a model that the estimated values should be close to actual values as much as possible. Therefore, the aim is to minimize the error, in other words, to diminish the difference between actual and estimated values. In this work, the prediction performance results of the time series based GMDH-type NN model for both the model development and testing stages were evaluated by using some performance criteria such as maximum negative error (MNE), maximum negative percentage error (MNPE), maximum positive error (MPE), maximum positive percentage error (MPPE), mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), root mean square percentage error (RMSPE), correlation (R), and coefficient of determination (R^2). Among them, R and R^2 values close to unity indicate a satisfactory result. Therefore, the highest values are anticipated for these criteria. In contrast, for other mentioned criteria, low value or value close to zero is desired for the forecasting model.

4. Results and Discussion

4.1 Results for Model Development and Testing Stages

Apart from the given information about model development in Section 3, some parameters of the GMDH-type NN model were set by the trial-error method to achieve the best model results. For this purpose, a number of experiments were executed by the changing number of folds in the validation strategy, neuron function, the maximum number of layers, and initial layer width. The best results were obtained for 2 folds, polynomial neuron function, the maximum layer of 500, and 3 initial layer width.

For these arrangements, the prediction results and residuals from the actual values are given in Fig.3. It is seen that predictions can capture seasonal changes in the years and have the ability to track the actual values. The performance criteria obtained for the model development stage are given in Table 2 and they support the judgment. For example, the maximum positive and negative percentage errors are far below 10 %. MAPE and RMSPE are approximately close to 2 % while R and R^2 values are above 0.95.

The results of the testing stage are depicted in Fig 4. It was understood from this figure that the model prediction results virtually compatible through the actual values. As seen in Table 2, although MNPE, MPPE, MAPE, and RMSPE values are better than the model development stage, R and R^2 values are slightly lower. Based on these performance results, the adequacy scale of the developed model can be evaluated as 'well level'.

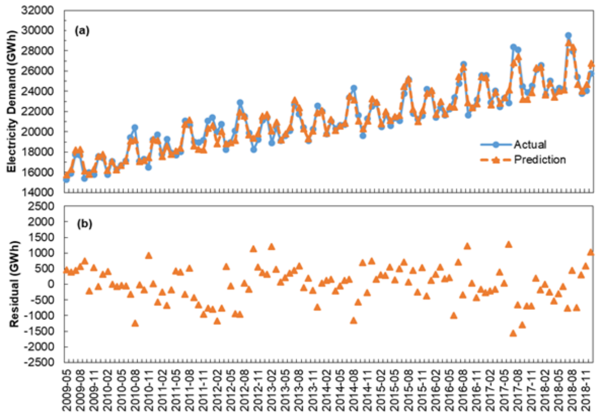

Figure 3. Model development results: (a) actual and prediction values, (b) residuals

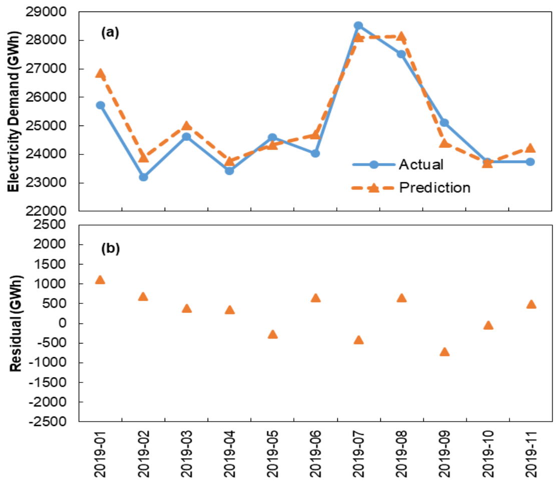

Figure 4. Testing results: (a) actual and prediction values, (b) residuals

Table 2. Performance results of model development and testing stages

Performance criteria	Symbol	Model development	Testing
Maximum negative error	MNE	-1563.33	-725.4
Maximum negative percentage error	MNPE	-6.10 %	-2.89 %
Maximum positive error	MPE	1285.76	1117.4
Maximum positive percentage error	MPPE	6.26 %	4.34 %
Mean absolute error	MAE	449.35	526
Mean absolute percentage error	MAPE	2.12 %	2.10 %
Root mean square error	RMSE	567.46	592.04
Root mean square percentage error	RMSPE	2.67 %	2.36 %
Correlation	R	0.983	0.946
Coefficient of determination	R^2	0.965	0.869

4.2 Comparison with A Study in The Literature

To show the generalization ability of the considered approach, the developed model was compared with a literature study performed by Hamzacebi et al. [26]. In the literature study, the seasonal ANN method was utilized to estimate the monthly electricity demand of Turkey for the period of 2015/01 – 2018/12 by using the dataset covering the period of 2002/01-2014/12. For comparison purposes, the GMDH-type model used in this study was reconfigured for the same forecasting period. The model was developed using the dataset covering the period of 2003/01-2014/12 to forecast the same period examined in the literature study. The number of folds, neuron function and initial layer width were set to 7, quadratic polynomial, and 3, respectively. Based on these arrangements, the GMDH-type NN model results were obtained. Fig.5 graphically shows the comparison of this study and the literature study in terms of the monthly electricity demand forecast. It can be seen in Fig.5(a) that the results of the GMDH-type NN model are superior to that of the literature study in the investigated period. Although the literature study can provide satisfactory results for the period of 2015/01-2015/12, its forecast performance is worsening in the later periods. The same outcomes can be observed when Fig.5(b) are examined. Although residuals of the GMDH-type NN model stay almost the same range throughout all periods, negative residuals of literature study are increasing. In addition, performance criteria of these two studies are compared in Table 3. Almost all criteria point out that the GMDH-type NN based model has a good capability to forecast the monthly electricity demand.

4.3 Forecasting for the Period of 2019/12 – 2020/12

The performed analyses had displayed that the GMDH-type NN model was the robust forecasting tool for the monthly electricity demand of Turkey. Therefore, the forecasting was executed by this model for the period of 2019/12- 2020/12. The forecasting results achieved by the GMDH-type NN model is depicted in Fig.6. According to this, in the investigated period, the trend in electricity demand is relatively the same for the year 2019. The confidence band indicating the difference of average forecast value from upper or lower one is 1134.92 GWh. Accordingly, it can be said that the peak electricity demand would be 28382 GWh in August of 2020, whereas the bottommost one could be 22995 GWh in November of 2020.

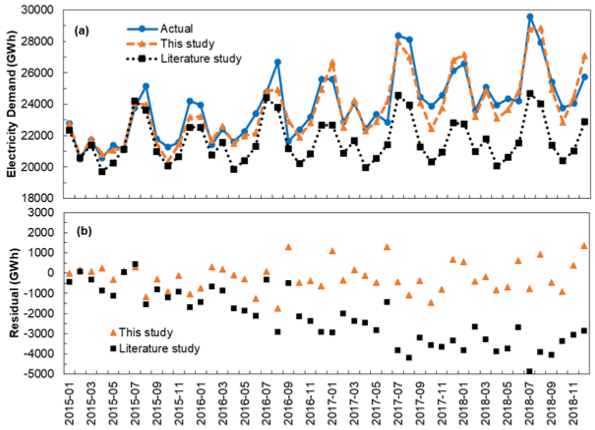

Figure 5. Comparison with the literature study: (a) actual and prediction values, (b) residuals

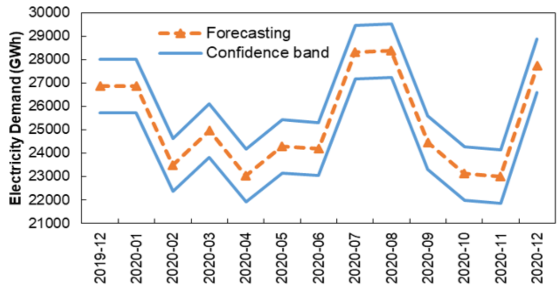

Figure 6. Forecasting results for the period of 2019/12 – 2020/12

Table 3. Comparison of the performance criteria of the studies

Performance criteria	Symbol	This study	*Hamzacebi et al. (2019)
Maximum negative error	MNE	-1746	-4872
Maximum negative percentage error	MNPE	-6.54 %	-16.48 %
Maximum positive error	MPE	1357	457
Maximum positive percentage error	MPPE	5.95 %	1.92%
Mean absolute error	MAE	596.92	2229.58
Mean absolute percentage error	MAPE	2.45 %	9.05 %
Root mean square error	RMSE	735.96	2573.13
Root mean square percentage error	RMSPE	3.00 %	10.24 %
Correlation	R	0.943	0.784
Coefficient of determination	R^2	0.877	0.615

*Performance criteria were calculated based on the forecast results given in the mentioned literature study.

The concept of GMDH-type NN might be a good tool to estimate the future electricity demand of Turkey. All energy-related institutions, especially the Turkish Ministry of Energy and Natural Resources may concern to use this research methodology in terms of strategic planning. In this way, this study can provide contribution not only to the academic research area but also to the practical life.

5. Conclusions

In this work, the GMDH-type NN approach was utilized to develop forecast model for the monthly electricity demand in Turkey. The developed forecasting model was established on the time series of the monthly electricity demand for the period of 2003/01-2018/12. The developed model was tested for the period of 2019/01-2019/11. In addition, to show the generalization capability, the forecasting results were compared with a literature study. The obtained outcomes from this work can be summarized below:

- In the model, development stage, main performance criteria such as MAPE, RMSPE and R^2 were obtained as 2.12 %, 2.67 % and 0.965, respectively.
- In the testing stage, the obtained forecasting performances were 2.10 % for MAPE, 2.36 % for RMSPE, and 0.869 for R^2.
- In the literature comparison, the used GMDH-type NN model provided higher forecasting performance compared to the seasonal ANN model used by the literature study. While the literature study provided 9.05 % for MAPE, 10.24 % for RMSPE, and 0.784 for R^2, GMDH-type NN model provided 2.45 %, 3 % and 0.943 for the same performance criteria, respectively.
- Based on the developed model, forecasting monthly electricity demand for the period of 2019/12 – 2020/12 were presented.

In light of the above results, it can be suggested that the GMDH type NN approach is appropriate to forecast the Turkey's monthly electricity demand. In future studies, the model forecasting capability can be enhanced by adding different input variables that influence the monthly electricity demand, such as price index, import and export data.

Declaration

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The author also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

A.V. Akkaya is responsible for all section of the study.

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