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Application of long short-term memory (LSTM) neural network based on deep learning for electricity energy consumption forecasting

Mehmet BILGILI[1,*], **Niyazi ARSLAN**[2], **Aliihsan SEKERTEKIN**[2], **Abdulkadir YASAR**[1]
[1]Department of Mechanical Engineering, Ceyhan Engineering Faculty, Cukurova University, Adana, Turkey
[2]Department of Geomatics Engineering, Ceyhan Engineering Faculty, Cukurova University, Adana, Turkey

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Abstract: Electricity is the most substantial energy form that significantly affects the development of modern life, work efficiency, quality of life, production, and competitiveness of the society in the ever-growing global world. In this respect, forecasting accurate electricity energy consumption (EEC) is fairly essential for any country's energy consumption planning and management regarding its growth. In this study, four time-series methods; long short-term memory (LSTM) neural network, adaptive neuro-fuzzy inference system (ANFIS) with subtractive clustering (SC), ANFIS with fuzzy c-means (FCM), and ANFIS with grid partition (GP) were implemented for the short-term one-day ahead EEC prediction. Root mean square error (RMSE), correlation coefficient (R), mean absolute error (MAE) and mean absolute percentage error (MAPE) were considered as statistical accuracy criteria. Those forecasted results by the LSTM, ANFIS-FCM, ANFIS-SC and ANFIS-GP models were evaluated by comparing with the actual data using statistical accuracy metrics. According to the testing process, the best MAPE values were obtained to be 4.47%, 3.21%, 2.34%, and 1.91% for the ANFIS-GP, ANFIS-SC, ANFIS-FCM, and LSTM, respectively. Furthermore, the best RMSE values were found as 25.94 GWh, 41.17 GWh, 29.50 GWh, and 80.14 GWh for the LSTM, ANFIS-SC, ANFIS-FCM, and ANFIS-GP models, respectively. As a consequence, the LSTM model generally outperformed all ANFIS models. The results revealed that forecasting of short-term daily EEC time series using the LSTM approach can provide high accuracy results.

Key words: Deep learning, electricity energy consumption, short-term forecasting, ANFIS, LSTM neural network

1. Introduction

Energy is amongst the fundamental requirements of the contemporary world, and it has an unquestionable critical role in industrial and technological development and economic progress. It has an influence on the quality and comfort of human life (https://www.iea.org) [1]. Energy is not only an unavoidable necessity for any country's internal dynamics but also a strategic issue that sometimes causes political debates and even military conflicts [2]. On the other hand, electricity, which is an important form of energy, cannot be physically stored. It is generally produced to the extent of need [3]. In an ever-growing global world, it significantly affects the quality of life of the society, the productivity of the business world, industrial and agricultural production, and the quality of competitiveness [4]. Furthermore, electrification is crucial for increasing the economic and social development of societies. The electricity sector gains a considerable amount of budget from the government and international development agencies. The sector has planned to invest almost $ 3.9 trillion in the period of 2021-2030 [5].

*Correspondence: mbilgili@cu.edu.tr

Recently, global electricity energy consumption (EEC) has been increasing due to the growth in population, emerging technologies, the progress of living standards and industrialization of the developing countries [6]. In this respect, the increase in electricity demand also requires a cheaper and safer electricity supply. Thus, predicting the electric charge is fairly essential for this aim. Literature survey shows that short-term accurate forecasting of EEC, which is one of the most substantial topics for today's developed and developing countries, ensures to carry out investments of the electricity sector properly [7]. In order to make important decisions on electricity production and scheduling, resource management, electricity purchasing, network security and stability in the grid energy management system, it is crucial to accurately build a prediction model for the EEC. In this sense, a simple and accurate EEC estimation model is required to obtain an accurate and reliable energy management system. In addition, a correctly predicted value can supply information for power system failures ensuring the smart grid's safe operation. Nonetheless, the nonstationary and linear features of the EEC series and its dependence on many variable components such as social activities, economic conditions, seasonal differences, weather, and time complicate the EEC forecast [8].

In recent years, researches have generally been performed on the analysis, planning and operation of electrical power systems to provide a reliable, uninterrupted, safe and economical electricity supply on the importance of the EEC, which is envisaged by various research communities [7]. For example, Kavaklioglu [4] depicted that avoiding the costly errors above-mentioned can be achieved by modeling the EEC with a high degree of accuracy. Tutun et al. [9] stated that the EEC should be forecasted with the optimum production model. Otherwise, estimation errors can lead to deficiencies or excess capacity in energy planning. Kaytez et al. [10] stated the EEC forecast, which forms the basis of energy investment planning, is an element that should be taken into consideration for developing countries. Yang et al. [11] depicted that the EEC estimate, which is a vital tool in the electricity market, not only reduces production costs but also has a key importance in power services. This can protect energy resources, which is important in terms of making forecasting methods crucial for the energy system. Considering the literature, the accurate estimation of EEC can prevent energy wastage and system failure. This situation is critical in case of no requirement to produce power above a certain level and in the absence of heavy load conditions in normal operation [12]. In addition, forecasting of EEC correctly leads to power grid planning, investment and transaction [13]. Mohan et al. [8] stated that the EEC forecasting only means obtaining a value for the expected future demand and primarily makes a long-term forecast of 5-20 years. The main purpose of EEC forecasting is managing the investment in power systems, long-term planning and resource management. Secondly, the mid-term forecasting from several months to certain years, e.g., 5 years, can be utilized for financial and operational planning, and energy generation. Thirdly, the short-term forecasting from several hours to weeks mainly concentrates on the planning and analysis of the distribution network. Furthermore, short-term EEC estimation contributes to improving management efficiency and reducing network operating costs that are needed for safe and reliable operation of the electricity network. An accurate short-term EEC forecasting model should be considered as nonlinear in order to evolve properties of the load series for predicting future demand efficiently [8, 10, 14].

Literature studies show that the significance of EEC forecasting methods has been gradually increasing in the world. Recently, many models have been proposed by researchers in order to forecast the EEC. In general, two major categories are valid for classification such as regression model and time series approach [5, 11]. In order to estimate the EEC with good precision in the regression model, some descriptive or independent variables that may affect EEC in that country must be accurately determined [15]. In general, independent indicators and historical data that are thought to be effective on the EEC should be considered for the model [10]. For example, although the population is amongst the highly correlated driving forces with the EEC, it is not enough to give a reason for the changes in the EEC over the years. In addition, it is ordinary to take some economic signs into account in connection with the EEC. Gross domestic product (GDP) is one of the factors that can be considered with this aim. Due to the increase in GDP per capita, people's living standards are improving and, accordingly, they become more dependent on devices that consume energy. Additionally, inflation rates, employment and electricity price are among the other economic factors that can change the EEC. On the other hand, climate situations such as the average temperature variations in winter and summer also influence the EEC. This situation causes more electricity consumption for irrigation and residential cooling depending on the high temperature in the summer months and more electricity consumption for electricity based heating of the residential due to the low temperature in the winter months [15]. Consequently, this regression model is not operational since the descriptive variables (e.g., population) for future predictions are uncertain. For this reason, the EEC is generally estimated by forecasting the descriptive variables for different scenarios, which are very arbitrary in some cases.

Concerning the time-series approach, the EEC or electricity demand can be considered as a function of the historical demand data to predict the probable future demand. In this method, even though results can be obtained correctly, the changes in electricity demand cannot be analyzed properly [15]. Literature studies on short-term EEC or electricity consumption forecasting are generally classified into 4 categories in terms of the forecasting techniques: (i) deep learning-based models, (ii) ensemble techniques, (iii) nonlinear methods, and (iv) linear methods [8]. The literature survey reveals that various forecasting tools depending on the regression model and time series approach were utilized for the prediction of the energy demand or future electricity [15–33]. Artificial neural network (ANN) [15–18, 22, 27, 29], linear regression (LR) [26], multiple linear regression (MLR) [15, 17, 22], multiple nonlinear regression (MNLR) [17, 22], random forest regression (RFR) [26], support vector regression (SVR) [4, 18, 19, 26], trigonometric grey model with rolling mechanism (TGMRM) [17], Holt-Winters exponential smoothing model (HWESM) [17], multilayered perceptron (MLP) regression [26], long short-term memory (LSTM) network [14, 19, 25, 27], structural time series model (STSM) [20], ANN with improved particle swarm optimization (ANN-IPSO) [5], ANN with teaching-learning-based optimization (ANN-TLBO) [21], seasonal auto-regressive iterative moving average (SARIMA) [9], nonlinear autoregressive ANN (NARANN) [9], grey model (GM) [23, 28], least squares support vector machines (LS-SVMs) [10], support vector machine (SVM) [27], wavelet neural network optimized by fruit fly optimization algorithm (WNN-FOA) [13], autoregressive integrated moving average (ARIMA) [13], improved empirical mode decomposition (IEMD) [13], back-propagation neural network (BPNN) [11], recurrent extreme learning machine (RELM) [24], recurrent neural network (RNN) [27], difference seasonal autoregressive integrated moving average (diff-SARIMA) [11], adaptive network-based fuzzy inference system (ANFIS) [11], ensemble empirical mode decomposition-LSTM (EEMD-LSTM) [26], empirical mode decomposition-LSTM (EMD-LSTM) [26], convolutional neural network-LSTM (CNN-LSTM) [30], LSTM with the differential evolution (DE-LSTM) algorithm [31], echo state network (ESN) [32], ESN improved by differential evolution (ESN-DE) algorithm [32], ESN improved by genetic algorithm (ESN-GA) [32], and the BPNN model supported by an adaptive differential evolution algorithm (ADE-BPNN) [33], methodologies have been widely applied for this purpose. On the other hand, deep learning approaches are used quite successfully in prediction studies that require high accuracy. Compared to traditional neural networks, deep learning is a very successful method in solving the problems of slow training speed and overadaptation [34, 35]. Recently, EEC has shown an increase in Turkey due to population growth and emerging technologies. In this regard, thanks to EEC planning, which is crucial for the country's energy policies, capacity planning can be made with low-cost investments. To achieve optimal planning, decision-makers have focused on modeling and predicting projections that can provide quality and trouble-free conditions [9]. As a result of estimating the energy demand correctly, the differences between supply and demand will have an adverse effect on the country's economy. When the electricity supply is higher than demand, this will cause excess energy and waste of available energy. Otherwise, the resulting energy deficit will bring about interruptions and system conflicts [36]. Moreover, Turkey's energy policy, which is a transit point between Europe and Asia, must have a solid foundation due to the increasing energy demand and strategic location. Rapid urbanization, industrialization, GDP, and population increase in the last twenty years have grown rapidly in the electricity market in Turkey. Ministry of Energy and Natural Resources (MINES) and the Ministry of Development (MD) is responsible for the prediction of long-term energy demand in Turkey. However, the development of reliable methods and alternative techniques are of great importance for Turkey's estimated future EEC [23]. Therefore, EEC forecasting studies over energy demand have become very important in recent years, especially for Turkey. Moreover, since Turkey is largely dependent on foreign sources of electricity generation, making the EEC accurate and precise forecasting is very important.

Currently, for Turkey, there are only a few studies in the literature to predict short-term daily EEC using the LSTM network based on deep learning. Thereby, the aims of the current study are (a) development of an LSTM model for Turkey's daily short-term EEC forecasting with high accuracy, (b) introducing a deep learning time series forecasting based on LSTM to investigate and use the implicit information of EEC time series for daily EEC forecasting. In this paper, the LSTM approach is proposed for daily EEC data series estimation to attempt a high level of abstraction from data given through a combination of various nonlinear transformations. In addition, in order to reveal the efficiency of the proposed approach, the results of the LSTM method were compared with the findings of the ANFIS-GP, ANFIS-SC and ANFIS-FCM models.

2. Methods and performance metrics

2.1. Adaptive neuro fuzzy inference system (ANFIS)

Jang [37] provided information on the ANFIS architecture and mechanism. ANFIS integrates the neural network (NN) with fuzzy logic. It approaches any true continuous function to any accuracy degree using nonlinear approach. ANFIS takes advantage of the superiority of FIS and ANN via converting them into a single system [38, 39].

The neuro-fuzzy model, utilized in this research, has five layers as a multilayered NN-based fuzzy system. The hidden layer nodes can be taken into account as MFs and rules. Typical ANFIS structure can be given in Figure 1. In this structure, a fixed node can be mentioned as a circle and an adaptive node can be represented as a square. The inputs are symbolized by x and y, while z is considered as one output. General information regarding ANFIS structure is available in the literature [37–40].

The Sugeno fuzzy model with first order and two if-then rules can be given by:

$$Rule\,1: if\; x\; is\; A_1\; and\; y\; is\; B_1, then\; z_1 = p_1 x + q_1 y + r_1 \tag{1}$$

$$Rule\,2: if\; x\; is\; A_2\; and\; y\; is\; B_2, then\; z_2 = p_2 x + q_2 y + r_2 \tag{2}$$

where A_i and B_i are the fuzzy clusters, p_i, q_i, and r_i are model's design variables specified in the training step. As stated above, the ANFIS structure consists of five layers:

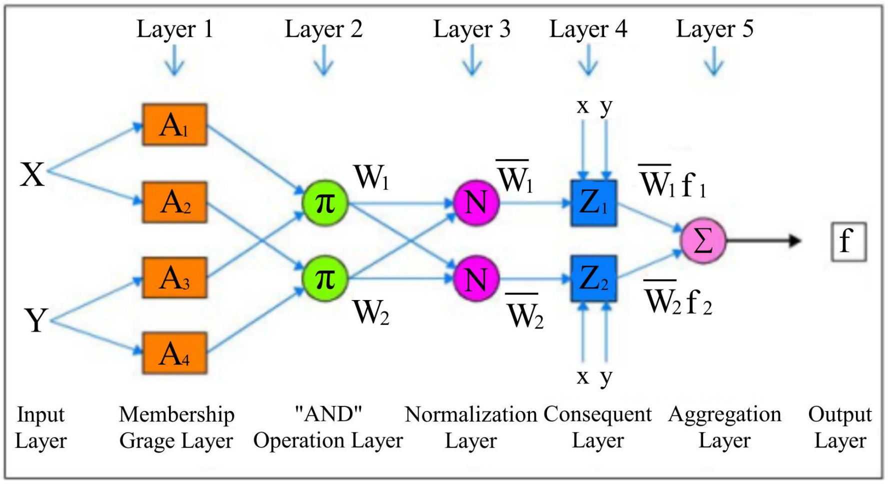

Figure 1. The illustration of the ANFIS architecture structure [40].

Layer 1: In this layer, an input parameter for each appropriate fuzzy set is mentioned via MFs that is presented by the nodes. The i^{th} node function with μ_{A_i} and μ_{B_i} MFs can be given as follows:

$$O_i^1 = \mu_{A_i}(x), \;\; i = 1, 2 \tag{3}$$

$$O_i^1 = \mu_{B_{i-2}}(y), \;\; i = 3, 4 \tag{4}$$

The variables in this layer are called preliminary variables.

Layer 2: In Layer 2, incoming signals from the Layer 1 are duplicated and forwarded to next layer. Each node computes a rule's firing strength, which adjusts the degree to which the rule matches the inputs, by multiplication.

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \;\; i = 1, 2 \tag{5}$$

Layer 3: In Layer 3, the i^{th} node computes the firing strength of the i^{th} rule's ratio to the sum of the firing strengths of all rules:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \;\; i = 1, 2 \tag{6}$$

where $\bar{w}_i$ is called the normalized firing strengths.

Layer 4: In Layer 4, node i determines the effect of i^{th} rule on the output via the node function shown below.

$$O_i^4 = \bar{w}_i z_i = \bar{w}_i(p_i x + q_i y + r_i), \;\; i = 1, 2 \tag{7}$$

$\bar{w}_i$ denotes the output of node i in Layer 3, and r_i, q_i, and p_i are named the consequent parameters.

Layer 5: In this layer, a single node's result as output is obtained from the sum of all coming signals:

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i z_i = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2} \tag{8}$$

As a result, the output z in Figure 1 can be given by:

$$Z = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \tag{9}$$

2.2. Long short-term memory (LSTM) neural network

In deep learning approaches, a different combination of nonlinear transformations is used to obtain a high level of information from the data. Deep neural network (DNN), LSTM, CNN, and RNN can be replaced by conventional signal processing methods in various research topics [41, 42].

The LSTM method is introduced by [43]. This method is a distinctive kind of RNN that deals with vanishing gradient issues in conventional RNN by adding memory cells or cell states with constant errors. The LSTM network is managed by input gate, output gate, and forget gate [44, 45]. The training processing is maintained until the minimum error or maximum epoch is achieved [44]. LSTM networks are effective in time-series forecasting [43]. LSTM neural network is formed by a connected series of LSTM units (Figure 2).

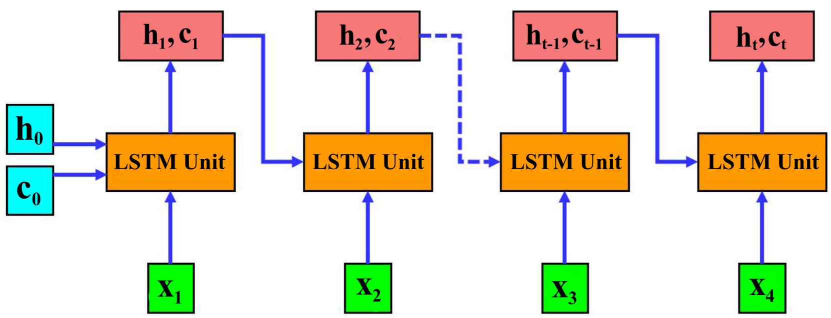

Figure 2. The architecture of LSTM network.

In Figure 2, $x = (x_1, x_2, x_3, , x_t)$, the time-series data, refers to input data, which is used for obtaining cell state $c = (c_1, c_2, c_3, , c_t)$ and hidden (output) state $h = (h_1, h_2, h_3, , h_t)$. The first input variable $x(x_1)$ is used to retrieve the first updated cell state (c_1) and the first value of the hidden state (h_1) in the first LSTM unit. At time step t, the LSTM unit is fed by h_{t-1} and c_{t-1} to acquire h_t and c_t. The hidden state (h_t) at time t is computed by:

$$h_t = o_t \odot tanh(c_t) \tag{10}$$

where $\odot$ is element-wise multiplication of vectors, named the Hadamard product. o_t is called the output gate, managing the cell state's level connected with the hidden state. The cell state adds to or removes information from the LSTM structure with the help of the gates to control the LSTM network. At the time step t, the cell state (c_t) involves knowledge from the previous units and is given by:

$$c_t = f_t \odot c_t - 1 + i_t \odot g_t \tag{11}$$

where forget gate (f_t) directs the degree of cell state reset, and input gate (i_t) manages the cell state update's level. Cell candidate (g_t) feeds the cell state by adding information. These are calculated by the following equations.

$$i_t = \sigma(W_i x_t + R_i h_{t-1} + b_i) \tag{12}$$

$$f_t = \sigma(W_f x_t + R_f h_{t-1} + b_f) \tag{13}$$

$$g_t = tanh(W_g x_t + R_g h_{t-1} + b_g) \tag{14}$$

$$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o) \tag{15}$$

where σ is the sigmoid function given by $sigma(x) = (1 + e^{(-x)})^{-1}$. R refers to the recurrent weights, while W is the input weights, and b is the bias. These parameters are shown in Equation 16.

$$W = \begin{vmatrix} W_i \\ W_f \\ W_g \\ W_o \end{vmatrix}, R = \begin{vmatrix} R_i \\ R_f \\ R_g \\ R_o \end{vmatrix}, b = \begin{vmatrix} b_i \\ b_f \\ b_g \\ b_o \end{vmatrix} \tag{16}$$

Figure 3 represents the structure a single LSTM unit obtained from Figure 2 (https://www.mathworks.com/help/deeplearning/ug/long-short-term-memory-networks.html). Generally, it is not simple to capture long-term time dependencies in time series during the implementation of RNNs. LSTM models have been designed to overcome this limitation. They are expressed as an extended version of RNN that can effectively handle time dependency in data. They are flexible and effective to explain time-dependent data and have been successfully applied in various fields of science. Furthermore, LSTM is one of the most applied RNN models for time series data prediction, which fits perfectly to EEC forecasting problems.

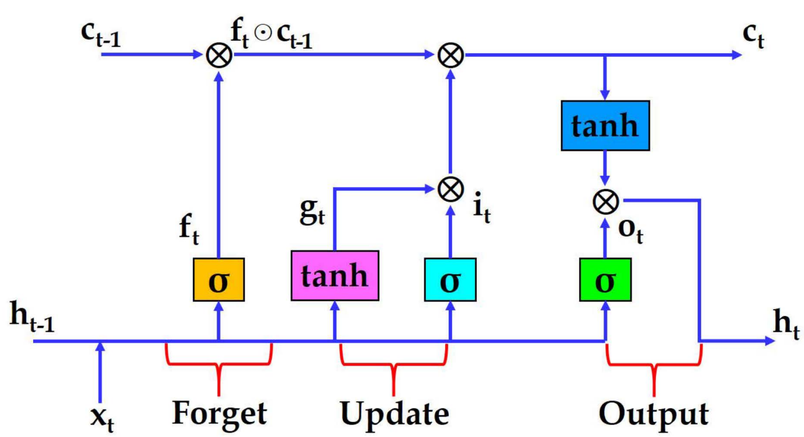

Figure 3. The structure of a single LSTM unit.

3. Material and experimental results

Electrical energy in Turkey is generated from power stations such as thermal, hydro, geothermal, wind and solar types, but there are no nuclear power plants for electricity production. Thermal and hydropower have the most rapidly growing installed capacities in the country. However, geothermal, solar and wind power have comparatively small installed capacities. While the cumulative installed capacity in Turkey was 33 MW in 1923, Turkey's overall electricity generation rose to $304,252$ GWh in 2019 (http://www.gwec.net). Keeping in mind the electricity generation of 2019, the thermal power plant ratio was 56.06%, corresponding to 170,555 GWh. On the other hand, hydropower accounted for 29.21%, corresponding to 88,886 GWh. Currently, the Turkish market has large natural gas, crude oil pipelines and other similar projects under negotiation. A total installed electricity generation capacity of about 10 GW is estimated to be available in the next decade according to the current regulatory framework, but this may even become 20 GW with amendments to the regulatory framework proposed by the Turkish Wind Power Association (http://www.gwec.net).

In this study, the LSTM and ANFIS methods are used to the EEC data for forecasting in Turkey. The EEC data were obtained from the Turkish Electricity Transmission Corporation (TETC) (http://www.teias.gov.tr), Turkey as daily basis from 1 January 2016 to 31 December 2019 without any missing data. Turkey's daily EEC ranged from 523.81 GWh to 979.21 GWh between 2016 and 2019. The minimum and maximum daily EEC was realized on September 12, 2016 and August 02, 2018, respectively. During these four years, the average and standard deviation of daily EEC were calculated as 785.39 GWh and 78.56 GWh, respectively.

In the LSTM and ANFIS applications, measurement data were split into training and testing datasets. The training dataset was used to train the model, while the testing dataset was used for over-fitting model validation. The RMSE, MAPE, MAE and R were used as statistical metrics to evaluate the model performances. The daily sampled EEC data from January 1, 2016 to December 31, 2019 were used to perform short-term daily EEC time series forecasting. The total 1460 measurements were split into two parts (25% as the test set and 75% as the train set).

In this study, the time-series technique was considered based on past observations of the EEC values as an input to train the model. The time-series approach may capture the stochastic component of the time series data and it may forecast the determinative part of the time series data. So, in this study, a forecasting model using machine learning and the time-series methods together is considered for the time series data of EEC. MATLAB R2018a (Trace Version) was used to realize these objectives and models. A summary of the developed and implemented program for the LSTM neural network is presented in Appendix A.

In this current study, the ANFIS model design was composed of training part and construction part. The number and type of membership functions (MFs) are determined in the construction section. Input/output data are divided into rule patches due to the nature of the ANFIS model. In the training part, training data pairs (inputs and related output) were first created to train an ANFIS model. In this study ANFIS with GP, SC, and FCM were implemented to achieve daily short-term EEC forecasting. The fuzzy approach of Sugeno was utilized to estimate the values for the output parameter from the given input data provided to the FIS structure. The transfer functions, the number of the hidden layer, the number of MFs, and the most suitable model structures were determined by trial and error. Then, the performance of the ANFIS models were evaluated via the statistical metrics. Gaussian membership function (Gaussmf) and linear membership function as input and output were used, respectively. Each training data sample set consists of 5 inputs and one output. The ANFIS membership functions after the training process are presented in Figure 4. As seen from the figure that the MF types of 5 inputs are a Gaussian function. Figures 5a and 5b present the RMSE criteria and loss function of the LSTM in terms of iteration numbers, respectively. It is seen from the figures that the RMSE value and the loss function converge when the number of periods is around 150.

According to the obtained results, the LSTM neural network is a successful deep learning approach based on a sophisticated network structure. It uses memory units in the model to capture time-series correlations. These memory units can store information over-time periods. While traditional methods perform the estimation without understanding the physical processes of the estimation domain, the LSTM neural network can

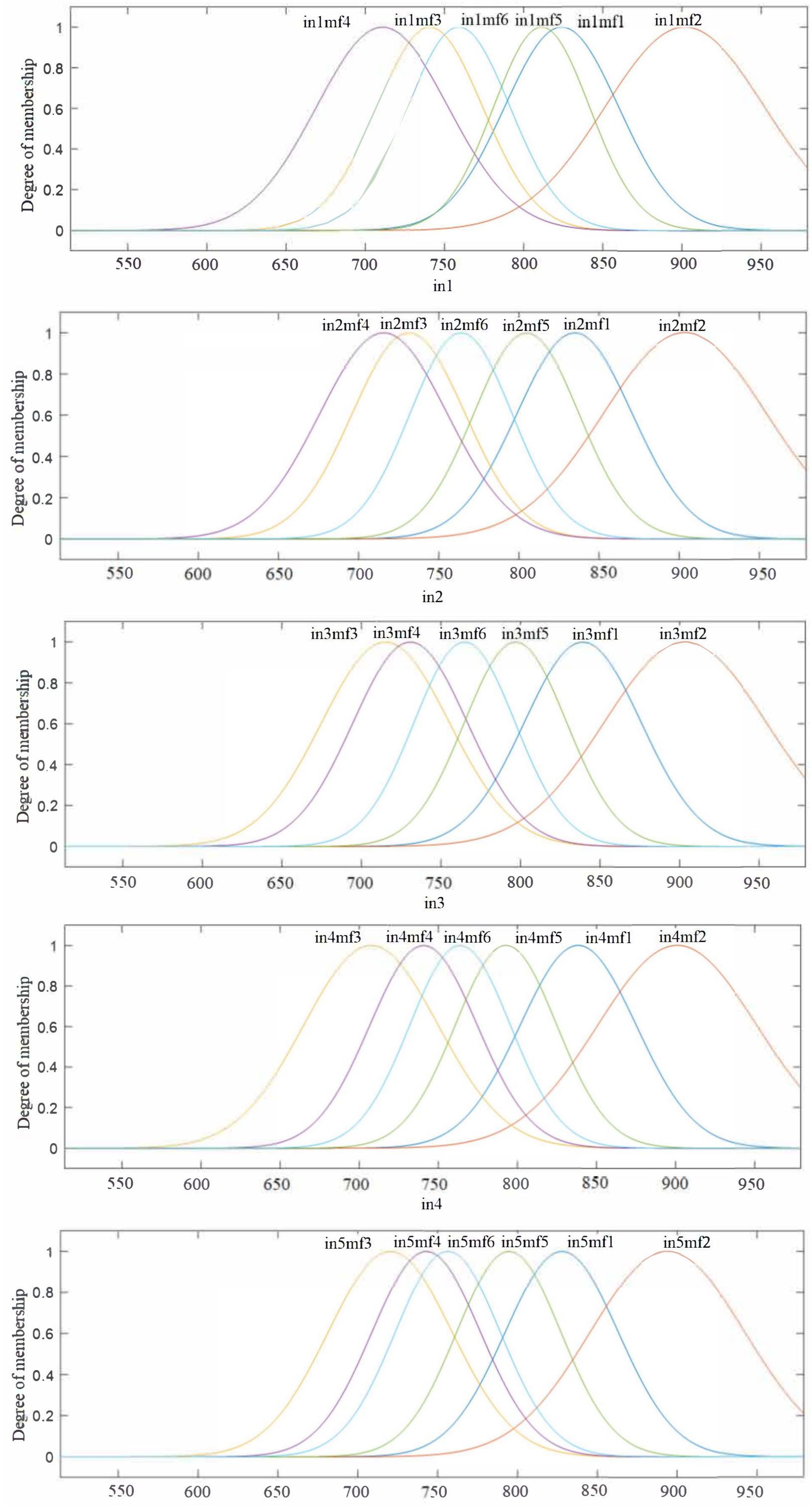

Figure 4. The ANFIS membership functions after the training process (number of MFs=6, input size=5).

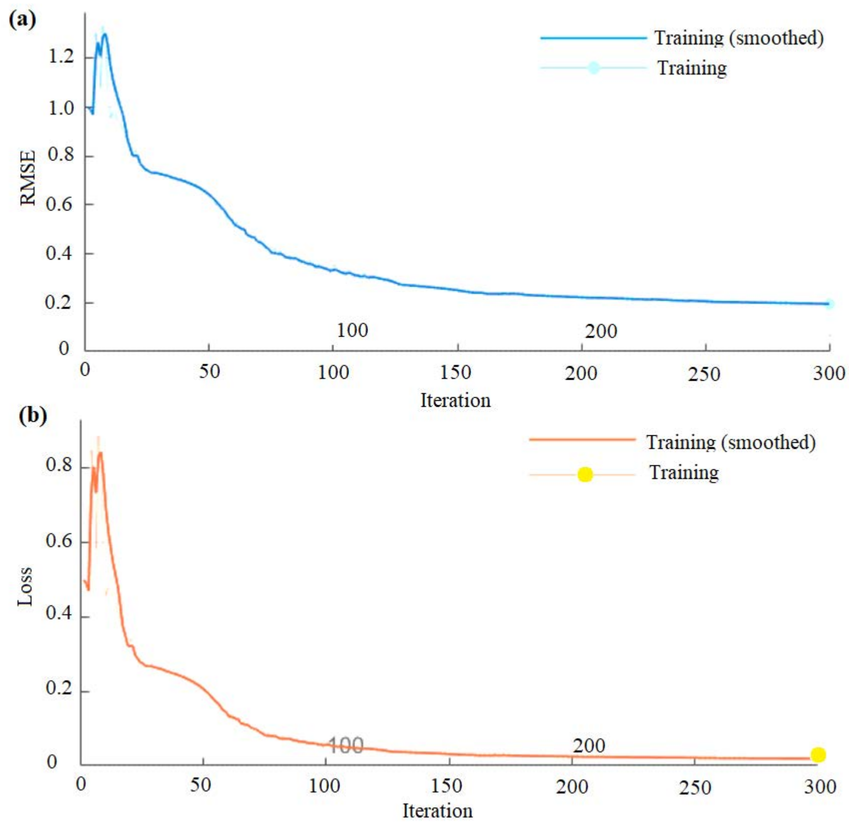

Figure 5. RMSE criteria and loss function curves in the training process of LSTM neural network.

comprehend the correlation between output data and input data automatically. The advantage of this feature has made LSTM the predictive model that is most widely applied in scientific research areas. In this regard, the LSTM neural network model has been successfully implemented in daily EEC forecasting due to its sophisticated network structure, ability to learn long-term behavior, and the ability to model the deterministic part of the time-series data.

The statistical evaluation criteria for the daily EEC forecasting are given in Table 1. The best results are given in bold by taking all metric results into account. The number of MFs for the ANFIS-FCM method was varied between 2 and 6. The quality metrics varied from 18.30 GWh to 19.69 GWh (MAE), 2.36 % to 2.51 % (MAPE), 29.50 GWh to 30.66 GWh (RMSE), and 0.9138 to 0.9201 (R), respectively. The best obtained RMSE is 29.50 GWh for MF=6 in ANFIS-FCM. It is clear that all the statistical quality metrics show similar results for this method. For the ANFIS-SC, the influence radius was considered between 0.2 and 0.7. The quality metrics were ranged from 25.01 GWh to 39.62 GWh (MAE), 3.21 % to 5.18 % (MAPE), 41.17 GWh to 50.54 GWh (RMSE), and 0.7362 to 0.8443 (R), respectively. The best obtained RMSE was 41.17 GWh in ANFIS-SC (influence radius equal to 0.4). There were discrepancies between the obtained results for this method. Furthermore, the statistical measures were 33.80 GWh (MAE), 4.47 % (MAPE), 80.14 GWh (RMSE), and 0.6076 (R), respectively, for the best result of the ANFIS-GP method (MF=2).

The selected hidden layer number in the LSTM neural network ranged from 50 to 250. The statistical metrics of LSTM neural network models were varied from 14.78 GWh to 16.45 GWh (MAE), 1.91% to 2.13%

Table 1. The statistical evaluation criteria for the daily EEC forecasting. The best results are shown in **bold**.

No	Model	Properties	MAE (GWh)	MAPE (%)	RMSE (GWh)	R
1	ANFIS-FCM	Number of MFs: 2	19.69	2.51	30.64	0.9171
2	ANFIS-FCM	Number of MFs: 3	18.93	2.44	30.19	0.9164
3	ANFIS-FCM	Number of MFs: 4	18.53	2.38	29.88	0.9180
4	ANFIS-FCM	Number of MFs: 5	18.30	2.34	30.66	0.9138
5	**ANFIS-FCM**	**Number of MFs: 6**	**18.37**	**2.36**	**29.50**	**0.9201**
6	ANFIS-SC	Influence radius: 0.2	25.01	3.21	42.53	0.8443
7	ANFIS-SC	Influence radius: 0.3	26.63	3.45	45.03	0.8207
8	**ANFIS-SC**	**Influence radius: 0.4**	**27.91**	**3.66**	**41.17**	**0.8383**
9	ANFIS-SC	Influence radius: 0.5	39.57	5.17	50.44	0.7374
10	ANFIS-SC	Influence radius: 0.7	39.62	5.18	50.54	0.7362
11	**ANFIS-GP**	**Number of MFs: 2**	**33.80**	**4.47**	**80.14**	**0.6076**
12	LSTM	Number of hidden layer: 50	16.45	2.13	29.04	0.9302
13	LSTM	Number of hidden layer: 100	14.81	1.91	26.65	0.9434
14	**LSTM**	**Number of hidden layer: 150**	**14.78**	**1.91**	**25.94**	**0.9480**
15	LSTM	Number of hidden layer: 200	16.04	2.06	28.49	0.9341
16	LSTM	Number of hidden layer: 250	16.07	2.08	29.59	0.9282

(MAPE), 25.94 GWh to 29.59 GWh (RMSE), and 0.9282 to 0.9480 (R), respectively. The best performance was obtained using the hidden layer number as 150 with the RMSE value of 25.94 GWh. It is clear that increasing of the hidden layer up to 150 contributes to the forecasting results with the improvement of the solution. If the hidden layer size more increases, the solution does not get higher accuracy, and the RMSE values are getting higher. Thus, it is crucial to choose optimal parameters to get high accuracy results from both the ANFIS and LSTM neural network. Besides, another important result in Table 1 is that all LSTM models provided higher accuracy than any ANFIS model.

Figures 6a, 6b, 6c, and 6d depict training and testing data with observed and forecasted daily EEC data for ANFIS-FCM, ANFIS-SC, ANFIS-GP, and LSTM methods, respectively. 1095 sample data were utilized as training data, whereas 365 sample data as testing data. The X-axis shows the daily variation of EEC time-series, while Y-axis states EEC values in GWh. The observed and forecasted values are shown in blue and red, respectively. The daily changes in energy consumption can be seen as a sinusoidal pattern. From Figures 6a, 6b, 6c, and 6d, it is clear that the forecasted EEC data almost overlap with the observed values in the testing part for all the methods. However, there are some spikes at forecasted values from ANFIS methods around the sudden changes in EEC. At that point, the LSTM values give better forecast results that can be seen as a lower value in RMSE. In general, the results show that the ANFIS methods and LSTM network model the daily EEC with good performance for this sinusoidal data. However, if we analyze the results taking into account RMSE values as 29.50 GWh (ANFIS-FCM), 41.17 GWh (ANFIS-SC), 80.14 GWh (ANFIS-GP), and 25.94 GWh (LSTM), the best results can be obtained from the LSTM network.

In order to visualize the quality of the forecasting in more detail, Figures 7a, 7b, 7c, and 7d are just given for testing data. Considering Figure 7, the spikes are much more in ANFIS-GP results than the other ANFIS

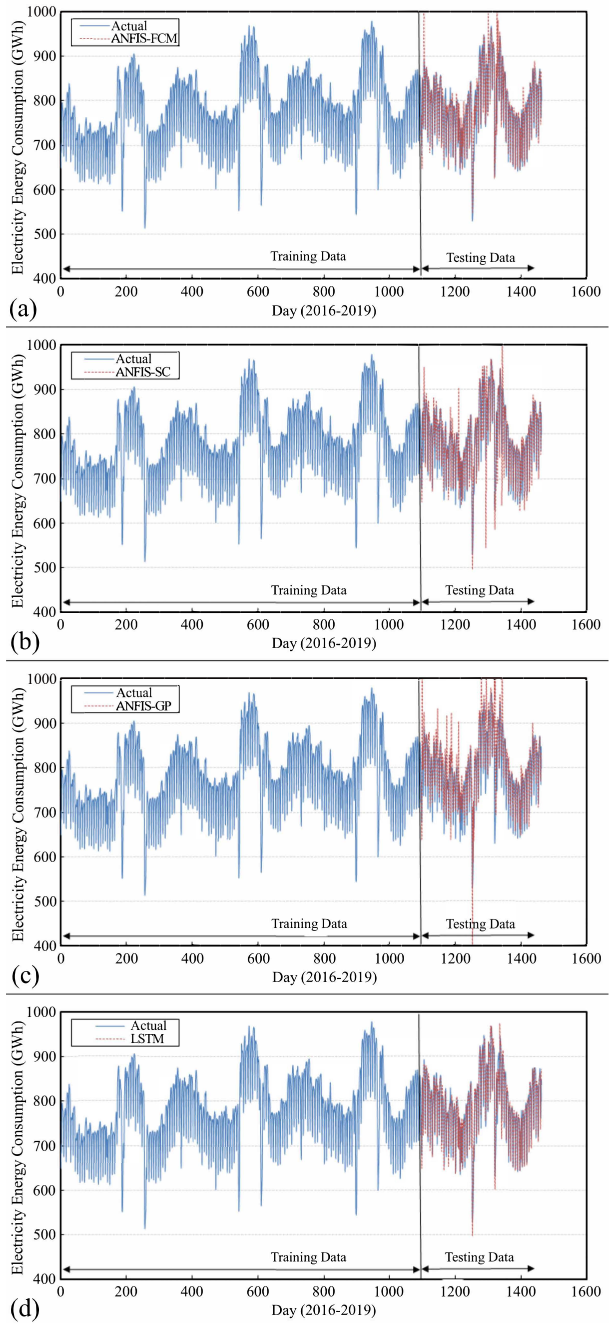

Figure 6. The daily EEC data of from January 1, 2016 to December 31, 2019 with observed (blue) and forecasted values (red) for (a) ANFIS-FCM, (b) ANFIS-SC (c) ANFIS-GP and (d) LSTM methods.

models (Figure 7c). There are almost no sharp spikes at the solution from the LSTM network (Figure 7d). The other two ANFIS methods have a few spikes that can be mentioned as quite satisfactorily (Figures 7a and 7b).

Figures 8a, 8b, 8c, and 8d show the regression plot of observed and forecasted daily EEC data for the LSTM, ANFIS-FCM, ANFIS-SC, and ANFIS-GP methods, respectively. The correlation coefficients (R) were obtained as 0.9480 (LSTM), 0.9201 (ANFIS-FCM), 0.8383 (ANFIS-SC) and 0.6076 (ANFIS-GP), respectively. It is clear from the figures that the best model fit to data was achieved by the LSTM neural network followed by the ANFIS-FCM model.

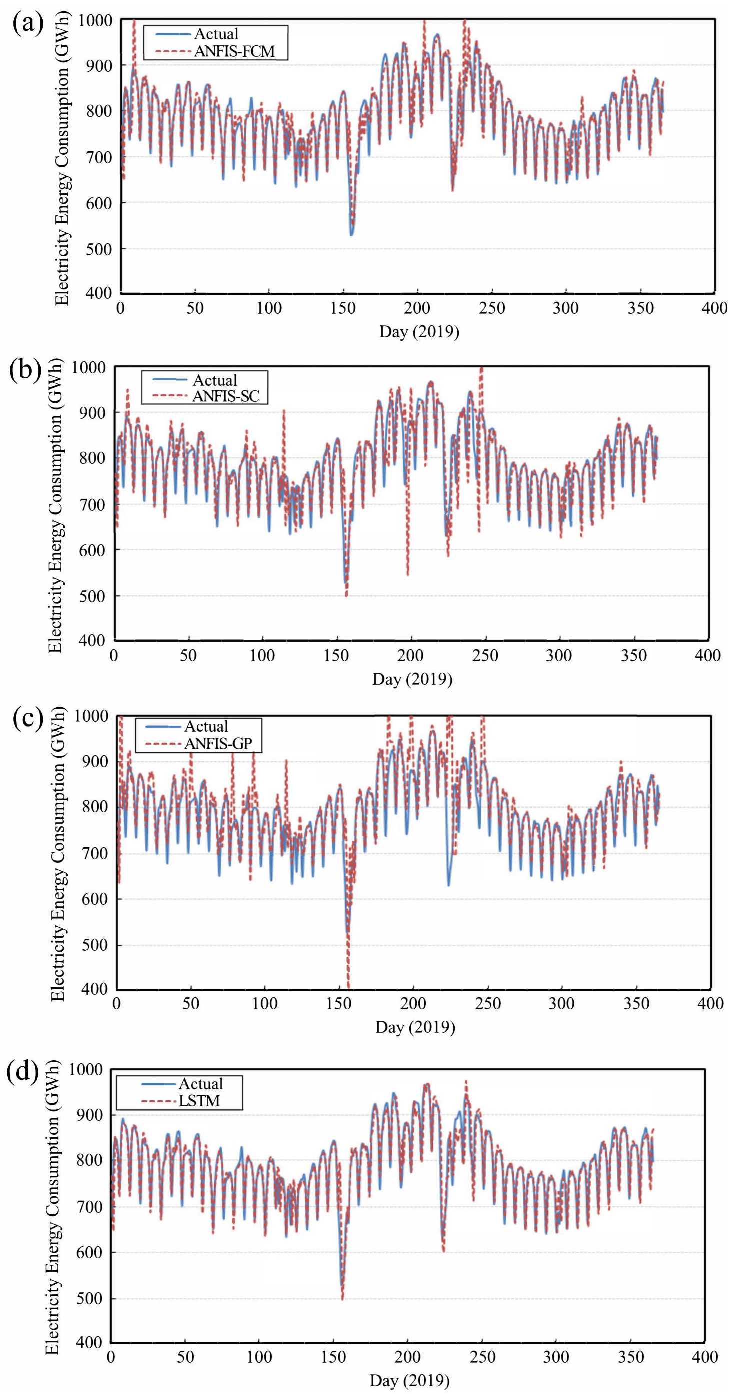

Figure 7. Observed (blue) and predicted values (red) of testing EEC data from (a) ANFIS-FCM, (b) ANFIS-SC (c) ANFIS-GP and (d) LSTM methods.

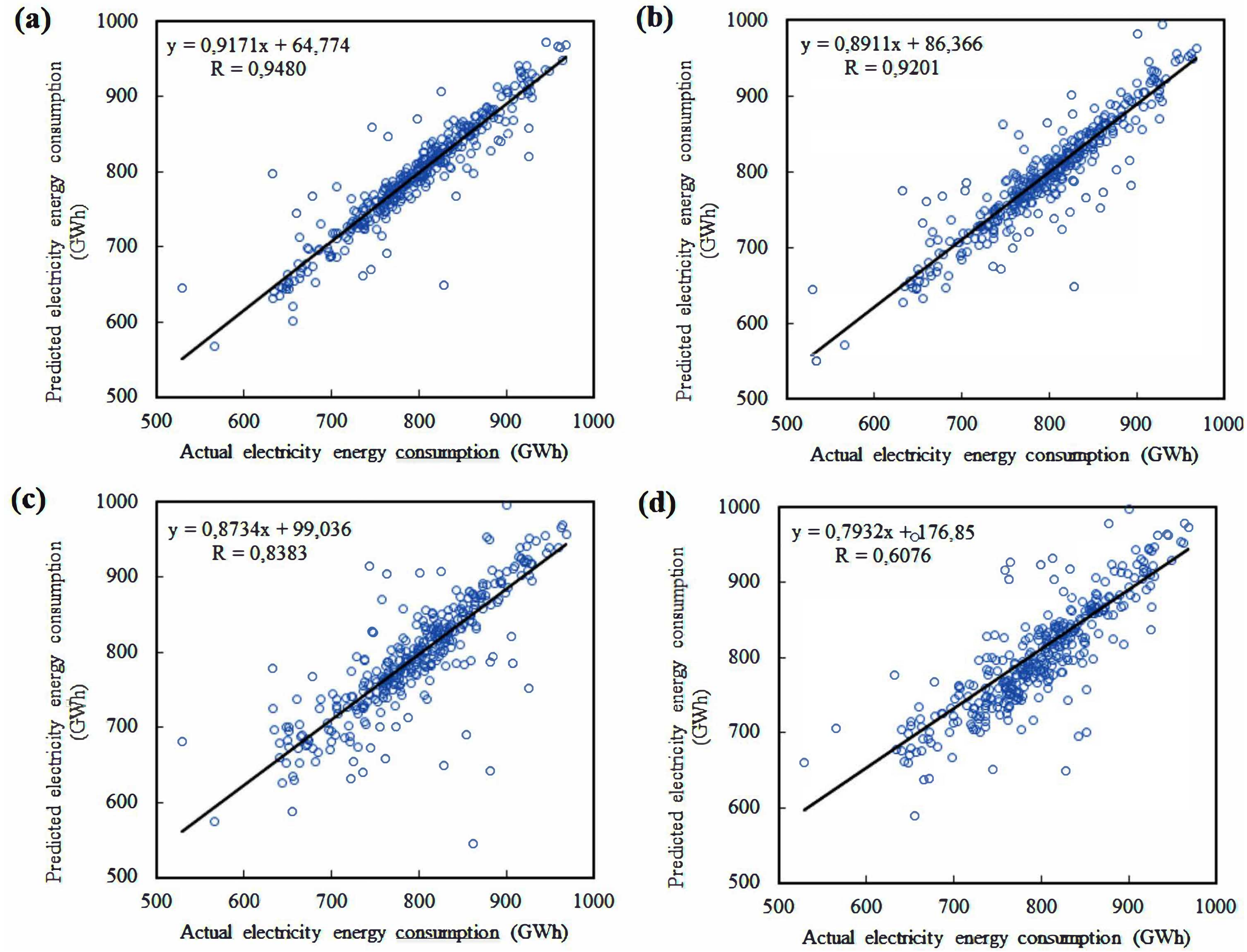

Figure 8. Regression plots of the observed and forecasted EEC values from (a) LSTM methods, (b) ANFIS-FCM, (c) ANFIS-SC and (d) ANFIS-GP.

Although a lot of studies related to the annual ECC forecasting for Turkey are available in the literature there are not many studies about the forecasting of short-term daily EEC time series. Nevertheless, the forecasting results of the proposed model are compared with the results obtained from some of the published studies based on monthly and annual EEC estimates, which are given in Table 2. The results show that the model in this study predicts daily EEC with close accuracy to models in other studies and even more accurately than most. As a summary, the results in this table showed that the proposed time-series prediction model was applied successfully for one-day ahead EEC forecasting.

4. Conclusion

Electricity is the most substantial energy form that significantly has an impact on the development of modern life, work efficiency, quality of life, production, and competitiveness of the society in the ever-growing global world. Therefore, forecasting accurate EEC is essential for any country's energy planning and management. In this study, LSTM neural network, ANFIS-SC, ANFIS-FCM, and ANFIS-GP methods were performed for forecasting the daily EEC data. The daily EEC data contained from 1 January 2016 to 31 December 2019

Table 2. Summary of typical studies on energy type forecasting.

Reference	Method	Forecasting energy type	Independent variables	Error criteria	Data
[4]	SVR	EEC	Population, year, gross national product, export and import	MAPE=1.51%	Yearly / 1975-2016
[9]	SARIMA, NARANN	EEC	Export, import, gross generation and transmitted energy	MAPE=1.60%	Yearly / 1975-2020
[10]	LS-SVMs	EEC	Population, gross electricity generation, total subscribership and installed capacity	MAPE=1.004%	Yearly / 1970-2009
[15]	ANN, MLR	Gross electricity demand	Winter and summer temperatures, inflation percentage, population, gross domestic product, unemployment percentage	RMSE=5.7 TWh	Yearly / 1975-2028
[16]	ANN	Sectorial EEC	Past data	MAPE=2.25%	Yearly / 1975-2020
[17]	ANN, MLR, MNLR	Energy consumption	Export, import, gross domestic product, population and employment	MAPE=1.222%	Yearly / 1980-2014
[18]	ANN, SVR	EEC	Past data, time index, seasonal index and month index	MAPE=3.3%	Monthly / 1970-2011
[19]	SVR, MLP, LSTM	Electricity production	Past data	R^2=0.91	Yearly / 1975-2017
[21]	ANN-TLBO	Energy consumption	Import, export, population and gross domestic product	MAPE=3.499%	Yearly / 1980-2020
[23]	GM	EEC	Past data	MAPE=6.381%	Yearly / 2014-2030
[28]	GM	EEC	Past data	MAPE=3.28%	Yearly / 1945-2025
[29]	ANN	Electricity demand	Population, gross domestic product, gross national product, energy consumption, number of tradeholds, IIP, crude oil prices and electricity price	MAPE=0.77%	Yearly / 1981-2007
[33]	ADE-BPNN	EEC and total energy consumption	Export, import, population and gross domestic product	MAPE=1.639%	Yearly / 1979-2006
This study	LSTM	EEC	Past data	MAPE=1.91%	Daily / 2016-2019

were obtained from the TETC. Total 1460 daily time-series data were split into two parts as 75 % training set and 25 % testing set. The obtained results showed that 75 % of the training data was enough for the accurate forecasting of the one-day ahead EEC. The optimal model parameters such as the epoch number, the number of MFs, and transfer functions were determined using trial and error. Considering the inter-comparison of the ANFIS models, ANFIS-FCM provided better results than ANFIS-GP and ANFIS-SC in forecasting the daily EEC. On the other hand, the LSTM network gave the best accuracy results amongst all models. The RMSE values of LSTM (25.94 GWh), ANFIS-GP (80.14 GWh), ANFIS-SC (41.17 GWh), and ANFIS-FCM (29.50 GWh) proved the highest performance of LSTM compared to the ANFIS models. Generally, this study has confirmed that different ANFIS models and the LSTM neural network are powerful tools in forecasting short-term daily EEC. As future works, hourly and monthly EEC data can be considered for both short-term and long-term predictions.

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