Mühendislik Bilimleri ve Tasarım Dergisi
9(2), 425 – 435, 2021
e-ISSN: 1308-6693

Journal of Engineering Sciences and Design
DOI: 10.21923/jesd.870908

Araştırma Makalesi Research Article

PREDICTION OF TURKEY'S ELECTRICITY GENERATION BY SOURCES USING ARTIFICIAL NEURAL NETWORK AND BIDIRECTIONAL LONG SHORT - TERM MEMORY

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Keywords
Energy Generation, Energy Sources, Electrical Energy, Artificial Neural Network, Prediction.

Abstract
It is an indisputable fact that energy plays a big role in the development of countries. Electrical energy has a great share in the development. Electricity is a secondary energy source, i.e. it is obtained by transforming primary energy sources. Although the desired level has not yet been reached, Turkey's installed power has increased by years and a wide variety of energy sources such as coal, oil, natural gas, hydroelectric energy, wind, solar and other renewable energy sources are used in electricity generation. At this point, it is observed that the share of renewable energy sources in total electricity generation has increased from year to year. It should be underlined that this increase is very important for the country's economy. In this study, Turkey's electricity generation by sources for the years 2020 and 2021 was predicted with artificial neural network (ANN) and bidirectional long short - term memory (BLSTM) methods using the data for electricity generation by sources in the years 2010-2019. The share of electricity generated from renewable energy sources in total electricity generation for 2020 by ANN and BLSTM methods was calculated as 18.08% and 18.6% respectively. For 2021, the share of electricity generated from renewable energy sources in total electricity generation was calculated as 21.95% and 21.68% respectively. These results show that the share of electricity generated from renewable energy sources in total electricity generation will increase. Finally, suggestions were made on what kind of roadmap should be followed in the field of investments in renewable energy resources.

TÜRKİYE'NİN KAYNAKLARA GÖRE ELEKTRİK ÜRETİMİNİN YAPAY SİNİR AĞI VE İKİ YÖNLÜ UZUN - KISA VADELİ BELLEK YÖNTEMLERİ KULLANILARAK TAHMİNİ

Anahtar Kelimeler
Enerji Üretimi, Enerji Kaynakları, Elektrik Enerjisi, Yapay Sinir Ağı, Tahmin.

Öz
Enerjinin ülkelerin gelişmesinde büyük bir rol oynadığı tartışılmaz bir gerçektir. Gelişmede elektrik enerjisine büyük pay düşer. Elektrik bir ikincil enerji kaynağıdır, yani birincil enerji kaynaklarının dönüştürülmesi sonucu elde edilmektedir. İstenen seviyeye ulaşılmamış olsa da Türkiye'nin kurulu gücü yıllara göre artmış ve elektrik üretiminde kömür, petrol, doğalgaz, hidroelektrik enerji, rüzgâr, güneş ve diğer enerji yenilenebilir enerji kaynakları gibi çok çeşitli enerji kaynakları kullanılmaktadır. Bu noktada toplam elektrik üretiminde yenilenebilir enerji kaynaklarının payının yıldan yıla arttığı gözlenmektedir. Bu artışın ülke ekonomisi için çok önemli olduğunun altı çizilmelidir. Bu çalışmada, Türkiye'nin 2010-2019 yıllarındaki kaynaklara göre elektrik üretimi verilerinden yararlanılarak 2020 ve 2021 yılları için kaynaklara göre elektrik üretimi, yapay sinir ağı (Artificial Neural Network - ANN) ve iki yönlü uzun – kısa vadeli bellek yöntemleri (Bidirectional Long Short - Term Memory - BLSTM) ile tahmin edilmiştir. ANN ve BLSTM yöntemleriyle 2020 yılı için yenilenebilir enerji kaynaklarından üretilen elektriğin toplam elektrik

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üretimi içindeki payının sırasıyla %18,08 ve %18,6 olacağı hesaplanmıştır. 2021 yılı için ise yenilenebilir enerji kaynaklarından üretilen elektriğin toplam elektrik üretimi içindeki payının sırasıyla %21,95 ve %21,68 olacağı hesaplanmıştır. Bu sonuçlar yenilenebilir enerji kaynaklarından üretilen elektriğin toplam elektrik üretimi içindeki payının artacağını göstermektedir. Son olarak yenilenebilir enerji kaynaklarına yatırımlar alanında nasıl bir yol haritası izlenmesi gerektiğine dair önerilerde bulunulmuştur.

Alıntı / Cite

Aylak, B. L., Özdemir, M. H., İnce, M., Oral, O. (2021). Prediction of Turkey's Electricity Generation by Sources Using Artificial Neural Network and Bidirectional Long Short - Term Memory, Journal of Engineering Sciences and Design ,9(2), 425-435.

Yazar Kimliği / Author ID (ORCID Number)	Makale Süreci / Article Process	
B. L. Aylak, 0000-0003-0067-1835	**Başvuru Tarihi / Submission Date**	29.01.2021
M. H. Özdemir, 0000-0002-7174-9807	**Revizyon Tarihi / Revision Date**	16.03.2021
M. İnce, 0000-0001-5566-5008	**Kabul Tarihi / Accepted Date**	30.03.2021
O. Oral, 0000-0002-6302-4574	**Yayım Tarihi / Published Date**	20.06.2021

1. Introduction

Energy sources are extremely important for economic and social development (Tunalı and Ulubaş, 2017). Humankind has needed energy since the earliest times and the demand for energy has increased gradually. This demand has been met by using a wide variety of energy sources (Yılmaz, 2012). There are various classifications for energy sources. One of these is the classification as non-renewable (fossil) sources and renewable sources (Koç and Şenel, 2013). While renewable energy sources mean energy sources that will not be exhausted in nature, non-renewable energy sources mean energy resources that will be exhausted after a certain period of time even if they are present in nature currently.

Renewable energy sources are environmentally friendly, but obtaining energy from these sources is still more expensive and more limited. On the other hand, energy production from non-renewable energy sources creates harmful wastes and causes greenhouse gas emissions (Bekar, 2020). However, in the face of increasing demand, fossil fuels are used to a large extent because they are more comfortable in energy production and, as stated, less costly (Çınar and Yılmazer, 2015). The data in Table 1 reveal that fossil fuels are used to a large extent. In the source, where the data are taken, hydroelectric energy is shown separately from renewable energy.

Table 1. Primary energy consumption by fuels in exajoules (EJ) in the world in 2018 and 2019 (BP, 2020a)

FUEL	2018		2019	
	ENERGY CONSUMPTION	SHARE (%)	ENERGY CONSUMPTION	SHARE (%)
OIL	191.45	33.22	193.03	33.06
NATURAL GAS	138.66	24.06	141.45	24.23
COAL	158.79	27.56	157.86	27.04
NUCLEAR ENERGY	24.16	4.19	24.92	4.27
HYDROELECTRIC	37.34	6.48	37.66	6.45
RENEWABLES	25.83	4.48	28.98	4.96
TOTAL	576.23	100	583.90	100

Another classification for energy sources is the classification made as primary and secondary energy sources (Koç and Kaya, 2015). Energy sources that can be used as they are in nature are called primary energy sources. Secondary energy sources are obtained by subjecting primary energy sources to various processes (Yapraklı and Yurttançıkmaz, 2012). Electricity can be generated by using various sources (Doğan, 2011). Therefore, electricity is a secondary energy source. However, electricity has an important place among energy sources. Electrical energy is applicable to many technologies, and it does not pollute the environment during its use. It has a wide field of consumption and an increase in electricity consumption was observed in parallel with developments in infrastructure investments in Turkey. Thus, the level of economic development of our country has also increased (Kar and Kınık, 2008). In 1902 electricity was generated in Tarsus district in Mersin for the first time by using a 2 kW dynamo connected to a water mill (Coşkun, 2012). Over time, installed power has increased and in parallel, electricity generation has also increased. As mentioned above, electrical energy can be generated by using various energy sources. Table 2 shows Turkey's electricity generation by sources for the period 2010-2019. (The numbers in Table 2 have been rounded up to four decimal places.) The column "Other renewables" include geothermal, biomass and other sources of renewable energy that are not already itemized. The column "Other" includes sources that are not specified elsewhere, e.g. pumped hydro, non-renewable waste and statistical discrepancies which can be positive or negative. As can be seen from Table 2, an increase in Turkey's electricity generation from year to year is observed. The very right column in Table 2 shows that the share of renewable energy sources in total electricity generation has increased from year to year.

Table 2. Turkey's electricity generation by sources in terawatt-hours (TWh) for the period 2010-2019 (BP, 2020b; BP, 2020c)

YEAR	OIL	NATURAL GAS	COAL	HYDROELECTRIC	RENEWABLES			OTHER	TOTAL ELECTRICITY GENERATION	SHARE OF RENEWABLES IN TOTAL ELECTRICITY GENERATION (%)
					WIND	SOLAR	OTHER RENEWABLES			
2010	2.1800	98.1437	55.0464	51.7955	2.9164	0.0024	1.0011	0.1246	211.2101	1.86
2011	0.9036	104.0476	66.2179	52.3386	4.7239	0.0029	1.0371	0.1264	229.3979	2.51
2012	1.6387	104.4992	68.0131	57.8650	5.8608	0.0043	1.4913	0.1288	239.5011	3.07
2013	1.7388	105.1163	63.7861	59.4205	7.5575	0.0068	2.2422	0.2926	240.1607	4.08
2014	2.1453	120.5760	76.2627	40.6447	8.5201	0.0174	3.4466	0.3501	251.9628	4.76
2015	2.2239	99.2187	76.1656	67.1458	11.6525	0.1941	4.6655	0.5171	261.7834	6.31
2016	1.9263	89.2271	92.2731	67.2309	15.5171	1.0431	6.4532	0.7369	274.4077	8.39
2017	1.1999	110.4900	97.4763	58.2185	17.9038	2.8893	8.2515	0.8482	297.2775	9.77
2018	0.3291	92.4828	113.2486	59.9385	19.9492	7.7998	10.0805	0.9734	304.8019	12.41
2019	0.1690	58.1172	114.5633	89.1593	21.7040	10.9196	12.7106	1.1253	308.4683	14.70

This study contributes a novelty to the literature with the feature of making the electricity generation prediction separately according to energy sources. In this study, Turkey's electricity generation by sources for the years 2020 and 2021 was predicted with artificial neural network (ANN) and bidirectional long short - term memory (BLSTM) methods using the data for electricity generation by sources in the years 2010-2019. Thus, it has been tried to predict which energy sources' share in electricity generation has increased or decreased. In this way, it was intended to shed light on investments in the energy field in Turkey.

This study consists of five sections. After the introduction, the second section includes a literature survey. In the third section, the material and method are explained, while the fourth section is devoted to the application. Finally, the fifth section contains results and discussion.

2. Literature Survey

There are many studies in the field of energy in which ANN is used to make predictions. Ringwood et al. (2001) forecasted short, medium and long term electricity demand for Ireland using ANN. Hsu and Chen (2003) formulated an ANN model to predict the regional peak load of Taiwan. Hamzaçebi and Kutay (2004) investigated the use of ANN in long-term electrical energy consumption forecasting. The results found with ANN were compared with those found by Box-Jenkins models and regression technique. The results have shown that ANN is a good forecaster of electrical energy consumption. Sözen et al. (2005) used two different ANN models to forecast net energy consumption in Turkey. In Model 1, population, gross generation, installed capacity and years are used in the input layer of the network. In Model 2, other energy sources are used in input layer of network. In both models, the net energy consumption is in the output layer. Pao (2006) used linear and nonlinear models including ANN to investigate the effect of national income, population, gross domestic production and consumer price index on the electricity consumption in Taiwan. It is shown that the ANN method is more suitable than the linear method for developing a electricity consumption forecasting model. Sözen et al. (2006) forecasted net energy consumption using the ANN technique. Population, gross generation, installed capacity and years are used in the input layer of network. The net energy consumption is in the output layer. Hamzaçebi (2007) forecasted Turkey's net electricity consumption on a sectoral basis using ANN because ANNs can forecast future values of more than one variable at the same time and model the nonlinear relation in the data structure. Sözen and Arcaklioglu (2007) used three different ANN models to predict net energy consumption in Turkey. In Model 1, installed capacity, generation, energy import and energy export are used in the input layer whereas gross national product in Model 2 and gross domestic product in Model 3 is used in the input layer of the network. For all models, the net energy consumption is in the output layer. Kavaklioglu et al. (2009) predicted electricity consumption of Turkey using ANNs. Electricity consumption is modeled as a function of population, gross national product, imports and exports. Geem and Roper (2009) proposed an ANN model to estimate the energy demand for South Korea. The model has gross domestic product, population, import and export amounts as independent variables. Kankal et al. (2011) modeled and forecasted Turkey's energy consumption based on socio-economic and demographic variables using ANN and regression analysis. Bilgili et al. (2012) applied ANN, linear regression and nonlinear regression models to estimate the electricity consumptions of the residential and industrial sectors in Turkey. Installed capacity, gross electricity generation, population and total subscribership are used as independent variables. Es et al. (2014) predicted the net energy demand of Turkey using ANN. Gross domestic product, population, imports, exports, building area and number of vehicles are used as inputs of the ANN model. Özden and Öztürk (2018) forecasted the energy demand in an industrial site (İvedik OSB) using ANN and time series method. Pençe et al. (2019) estimated the electricity consumption for the 2017-2023 period using an ANN model with data for the 1970-2016 period. In his master's thesis, Yüzük (2019) predicted Turkey's electricity consumption using multiple regression analysis and ANN with electricity data held on a monthly basis between the years 2010-2017. Kayakuş (2020) estimated Turkey's energy demand using ANN and support vector regression. 15 independent variables are used as inputs and Turkey's energy consumption value as the dependent variable is estimated.

3. Material and Method

In this study, Turkey's electricity generation by sources for the years 2020 and 2021 was predicted with ANN and BLSTM methods using the data for electricity generation by sources in the years 2010-2019. In this section, ANN and BLSTM methods are explained.

3.1. Artificial Neural Networks

ANNs are an artificial intelligence and machine learning method by imitating biological nerve cells (Esfe et al., 2015). ANNs generally contain an input layer, one or multiple hidden layers, and an output layer, neurons in these layers and weights (Figure 1). With this method, prediction and classification can be made with the aid of existing data. After training the system with real data, it is expected to obtain outputs suitable for the test data of the system. There is a large number of application areas for ANNs, i. e. skin cancer level determination (Esteva et al., 2017), detection of automobile engine faults (Ahmed et al., 2014), drug classification (Byvatov et al., 2003), electric load estimation (Park et al., 1991), stock market forecast (Ticknor, 2013), wind speed estimation (Khosravi et al., 2018) and electricity energy demand forecasting (Özden and Öztürk, 2018).

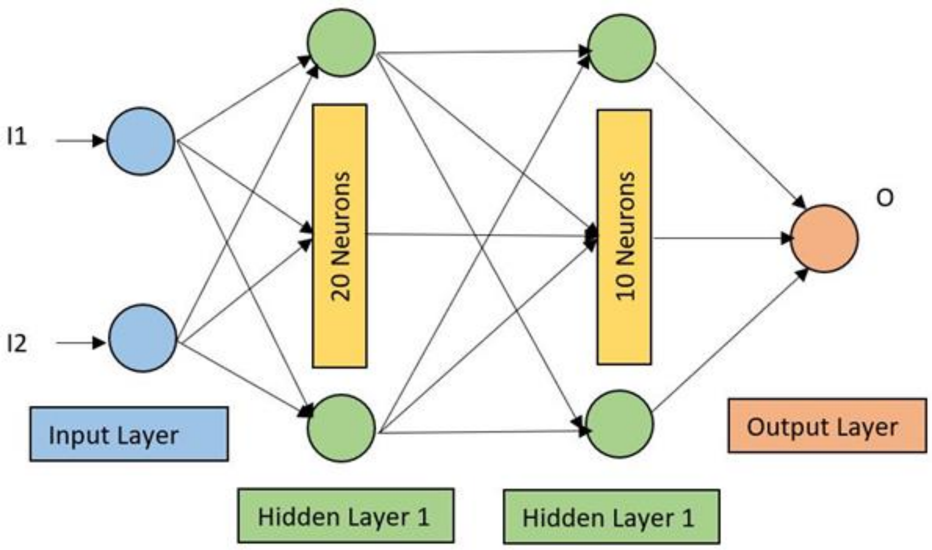

Figure 1. Network structure 2-20-10-1

3.2. Bidirectional Long-Short Term Memory

Deep learning is another popular algorithm inspired by ANNs. Deep learning is used in many areas such as image processing, classification and natural language processing (Deng and Yu, 2014). Deep learning networks distinguish from classical ANNs in many ways, such as number of layers (LeCun et al., 2015). The most used deep learning algorithms are Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). A particular version of the regular RNN is Long-Short Term Memory. Normal (One-Way) LSTMs can fail in sequential operations such as time series since they do one operation (Graves and Schmidhuber, 2005). Bidirectional LSTMs run two LSTMs on the same input data in time series problems (Figure 2). The first LSTM runs on the input data from back to forward, while the second LSTM runs on the same data from forward to back (Kiperwasser and Goldberg, 2016). In this way, by running two LSTMs on the same input data, the system is provided to be faster and the learning deficiencies in one-way LSTM are completed.

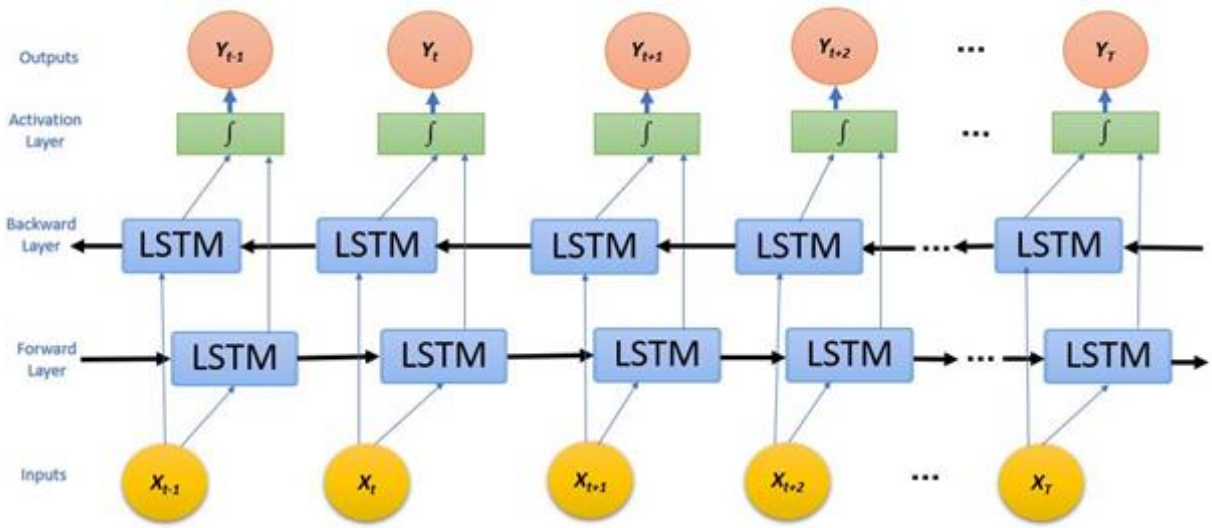

Figure 2. BLSTM structure (Graves and Schmidhuber, 2005)

4. Experimental Results

In this study, Turkey's data on electricity generation from different sources for the period 2010-2019 are used to predict the electricity generation for the years 2020 and 2021. As the data were collected from an online database, an Ethics Committee Permission is not required in this study. Since the limited and one-dimensional data available are a time series, it is necessary to make use of historical data for prediction. Firstly, the data were transformed into a series with two elements. Then ANN and BLSTM methods were applied to these series.

In both methods, the values of electricity generated from oil in successive years in Table 2 were used as two inputs I1 and I2. The value of electricity generated from oil in the following year after these consecutive years was used as the only output O (Table 3). The values of I1, I2, and O in the first row in Table 3 are the values of electricity generated from oil for the years 2010, 2011 and 2012 respectively. While I2 in the first row is used as the first input in the second row, O in the first row is now used as the second input in the second row. This shifting is repeated for the remaining six rows. In other words, the values in the first row are from 2010, 2011, and 2012, respectively, while those in the second row are from 2011, 2012, and 2013. This process is continued until 2019. Thus, the data series to be used in the method is produced. In Tables 4-10, the data set was produced for other energy sources in the same way using the data in Table 2.

Table 3. Two-element data set values of electricity generated from oil in the period 2010-2019

I1	I2	O
2.1800	0.9036	1.6387
0.9036	1.6387	1.7388
1.6387	1.7388	2.1453
1.7388	2.1453	2.2239
2.1453	2.2239	1.9263
2.2239	1.9263	1.1999
1.9263	1.1999	0.3291
1.1999	0.3291	0.1690

Table 4. Two-element data set values of electricity generated from natural gas in the period 2010-2019

I1	I2	O
98.1437	104.0476	104.4992
104.0476	104.4992	105.1163
104.4992	105.1163	120.5760
105.1163	120.5760	99.2187
120.5760	99.2187	89.2271
99.2187	89.2271	110.4900
89.2271	110.4900	92.4828
110.4900	92.4828	58.1172

Table 5. Two-element data set values of electricity generated from coal in the period 2010-2019

I1	I2	O
55.0464	66.2179	68.0131
66.2179	68.0131	63.7861
68.0131	63.7861	76.2627
63.7861	76.2627	76.1656
76.2627	76.1656	92.2731
76.1656	92.2731	97.4763
92.2731	97.4763	113.2486
97.4763	113.2486	114.5633

Table 6. Two-element data set values of hydroelectricity generated in the period 2010-2019

I1	I2	O
51.7955	52.3386	57.8650
52.3386	57.8650	59.4205
57.8650	59.4205	40.6447
59.4205	40.6447	67.1458
40.6447	67.1458	67.2309
67.1458	67.2309	58.2185
67.2309	58.2185	59.9385
58.2185	59.9385	89.1593

Table 7. Two-element data set values of electricity generation from wind in the period 2010-2019

I1	I2	O
2.9164	4.7239	5.8608
4.7239	5.8608	7.5575
5.8608	7.5575	8.5201
7.5575	8.5201	11.6525
8.5201	11.6525	15.5171
11.6525	15.5171	17.9038
15.5171	17.9038	19.9492
17.9038	19.9492	21.7040

Table 8. Two-element data set values of solar electricity generated in the period 2010-2019

I1	I2	O
0.0024	0.0029	0.0043
0.0029	0.0043	0.0068
0.0043	0.0068	0.0174
0.0068	0.0174	0.1941
0.0174	0.1941	1.0431
0.1941	1.0431	2.8893
1.0431	2.8893	7.7998
2.8893	7.7998	10.9196

Table 9. Two-element data set values of electricity generated from other renewables in the period 2010-2019

I1	I2	O
1.0011	1.0371	1.4913
1.0371	1.4913	2.2422
1.4913	2.2422	3.4466
2.2422	3.4466	4.6655
3.4466	4.6655	6.4532
4.6655	6.4532	8.2515
6.4532	8.2515	10.0805
8.2515	10.0805	12.7106

Table 10. Two-element data set values of electricity generated from other sources in the period 2010-2019

I1	I2	O
0.1246	0.1264	0.1288
0.1264	0.1288	0.2926
0.1288	0.2926	0.3501
0.2926	0.3501	0.5171
0.3501	0.5171	0.7369
0.5171	0.7369	0.8482
0.7369	0.8482	0.9734
0.8482	0.9734	1.1253

Different number of layers and neurons were tested in the training phase in order to obtain the best prediction in ANN method. Parameters, which give the best prediction, are chosen as ANN parameters. Thus, two inputs, one output and two hidden layers with 20 and 10 neurons respectively were used to form a network structure of 2-20-10-1 (Figure 1). Learning rate was adjusted as 0.5 and the sigmoid was used as activation function. It was carried out with 200 epochs during ANN training, and from the data for the years 2017 and 2018, a value of 0.1712362 was predicted for the actual value of 0.169 in 2019 with a relative error of 1.32% (Table 11). Then, BLSTM method was trained with 50 epochs, and Adam optimizer was used. Instead of the classical stochastic gradient reduction method, Adam is a more efficient, adaptive optimization algorithm, i.e. it updates the learning rate for each parameter (Kingma and Ba, 2014; Ruder, 2016). By this method, a value of 0.170484 was predicted for the actual value of 0.169 in 2019. A relative error of 0.88% has been found after comparing both values (Table 11). As can be seen in Table 11, the BLSTM method gives better results than the ANN method for all predictions of the value of electricity generated from various sources.

Table 11. Predictions of the value of electricity generated from various sources in 2019

SOURCE	2019 ACTUAL VALUE	2019 PREDICTIONS			
		ANN		BLSTM	
		VALUE	RELATIVE ERROR (%)	VALUE	RELATIVE ERROR (%)
OIL	0.1690	0.1712362	1.32	0.170484	0.88
NATURAL GAS	58.1172	59.2442173	1.94	58.600586	0.83
COAL	114.5633	113.9419604	-0.54	115.013535	0.39
HYDROELECTRIC	89.1593	61.2766661	-31.27	69.08673	-22.51
WIND	21.7040	20.7803807	-4.26	21.78258	0.36
SOLAR	10.9196	10.689053	-2.11	10.899599	-0.18
OTHER RENEWABLES	12.7106	12.0189666	-5.44	12.6317005	-0.62
OTHER	1.1253	1.0572592	-6.05	1.1144639	-0.97

ANN and BLSTM methods were used to predict the value of the electricity generated for 2020 from the data for 2018 and 2019 with the same training and optimization parameters (Table 12). Similarly, the value for 2019 and the predicted value for 2020 are used to predict the value of the electricity generated in 2021 from all different sources with the same training and optimization parameters (Table 12). The actual values for 2020 and 2021 are unknown.

Table 12. Predictions of the value of electricity in TWh generated from various sources for 2020 and 2021

SOURCE	2020 PREDICTIONS		2021 PREDICTIONS	
	ANN	BLSTM	ANN	BLSTM
OIL	0.21418289	0.2076833	0.25271984	0.2456418
NATURAL GAS	65.23079431	65.27646	58.54790882	60.756832
COAL	121.8642145	124.37067	129.5088635	138.93199
HYDROELECTRIC	87.10565718	86.88384	91.94973769	93.227936
WIND	24.7860188	26.758623	30.63023481	31.310879
SOLAR	21.06665163	21.294617	30.84545502	31.787287
OTHER RENEWABLES	14.97739043	15.445854	17.67159741	18.377289
OTHER	1.11801605	1.1475525	1.13545079	1.1518936
TOTAL	336.3629258	341.3852998	360.5419679	375.7897484

As mentioned before, the BLSTM method yielded better predictions for the value of electricity generated from various sources in 2019 in comparison of the ANN method. Since the values for 2020 and 2021 are unknown, it cannot be determined which method gives better prediction values.

5. Result and Discussion

In this study, electricity generation by energy sources was predicted for 2020 and 2021 using ANN and BLSTM methods. According to analysis, it was observed that the BLSTM method gave better results than the ANN method in 2019 for all energy sources. Prediction values of electricity generation for 2020 and 2021 were calculated with the best ANN network structure and BLSTM parameters obtained from 2019 predictions.

As mentioned in the introduction, the share of electricity generated from renewable energy sources in total electricity generation is increasing year by year. This increase contributes to the Turkish economy by reducing foreign dependency. It is also a good development in terms of reducing the damage to the environment. Considering the predicted values obtained by both the ANN method and the BLSTM method for the years 2020 and 2021, it is observed that the share of electricity generated from renewable energy sources in total electricity generation has increased. According to the results found by ANN and BLSTM methods for 2020, it is predicted that the share of electricity generated from renewable energy sources in total electricity generation will be 18.08% and 18.6%, respectively. For 2021, according to the results obtained by ANN and BLSTM methods, it is predicted that the share of electricity produced from renewable energy sources in total electricity generation will be 21.95% and 21.68%, respectively. The outbreak, which has affected the whole world, may have a negative impact on the electricity generation. For this reason, it can be concluded that there is a difference between the total electricity generation value and the predicted value for 2020. Furthermore, fluctuations in hydroelectricity generation can be shown as another reason for the difference between the predicted value and the actual value in 2020 and 2021.

In accordance with the goal of Affordable and Clean Energy, one of the Sustainable Development Goals of the United Nations, investments should be made in clean energy sources such as solar, wind and thermal energy in order to ensure that everyone can access energy by 2030. The necessity of investing into the field of renewable energy in Turkey has been confirmed by the results in this study.

Turkey has not only high solar energy potential but also high wind energy potential. In addition, it is practical and easy to generate electricity directly from these two energy sources. From this point of view, in future studies, especially the regions with high wind and solar energy potential can be determined and predictions for the electricity generation and the installed power in these regions can be made accordingly.

Conflict of Interest

No conflict of interest was declared by the authors.

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