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INSTALLED SOLAR POWER PREDICTION FOR TURKEY USING ARTIFICIAL NEURAL NETWORK AND BIDIRECTIONAL LONG SHORT-TERM MEMORY

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ABSTRACT

Renewable energy sources play an essential role in sustainable development. The share of renewable energy-based energy generation is rapidly increasing all over the world. Turkey has a great potential in terms of both solar and wind energy due to its geographical location. The desired level has not yet been reached in using this potential. Nevertheless, with the increase in installed power in recent years, electricity generation from solar energy has gained momentum. In this study, data on cumulative installed solar power in Turkey in the 2009-2019 period were used. Artificial Neural Network (ANN) and Bidirectional Long Short-Term Memory (BLSTM) methods were selected to predict the cumulative installed solar power for 2020 with these data. The cumulative installed power was predicted, and the results were compared and interpreted.

Keywords:

Renewable Energy, Solar Energy, Prediction, Artificial Neural Network

JEL Codes:

O20, Q42, Q47

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TÜRKİYE İÇİN GÜNEŞ ENERJİSİ KURULU GÜCÜNÜN YAPAY SİNİR AĞI VE İKİ YÖNLÜ UZUN- KISA VADELİ BELLEK KULLANILARAK TAHMİNİ

ÖZ

Sürdürülebilir bir kalkınma için yenilenebilir enerji kaynakları önemli bir rol oynamakta ve yenilenebilir enerji kaynaklı enerji üretiminin payı tüm dünyada hızla artmaktadır. Ülkemiz, bulunduğu coğrafi konumu nedeniyle hem güneş hem de rüzgâr enerjisi açısından büyük bir potansiyele sahiptir. Bu potansiyeli kullanma konusunda henüz istenen düzeye ulaşılamamıştır. Yine de son yıllarda kurulu gücün artmasıyla birlikte güneş enerjisinden elektrik üretimi çalışmaları hız kazanmıştır. Bu çalışmada, Türkiye'nin 2009-2019 yılları arasındaki kümülatif güneş enerjisi kurulu gücü verileri kullanılmıştır. Bu veriler ile 2020 yılı için kümülatif kurulu gücü tahmin etmek amacıyla Yapay Sinir Ağı (Artificial Neural Network - ANN) ve İki Yönlü Uzun-Kısa Vadeli Bellek (Bidirectional Long Short-Term Memory - BLSTM) yöntemleri kullanılmıştır. Kümülatif kurulu güç tahmin edilmiş ve sonuçlar karşılaştırılarak yorumlanmıştır.

Anahtar Kelimeler:

Yenilenebilir Enerji,

Güneş Enerjisi,

Tahmin,

Yapay Sinir Ağı

JEL Kodları:

O20, Q42, Q47

1. INTRODUCTION

The energy needs of countries are increasing day by day. As a result of increasing consumption, fossil energy resources in the world are rapidly running out. Nevertheless, fossil energy resources still have a considerable share in primary energy consumption across the world. Primary energy consumption by sources in 2018 and 2019 is shown for the entire world in Figure 1 and Figure 2. As can be seen from the Figures, the primary energy consumption originating from fossil energy resources is over 80% in both years. Moreover, Turkey's primary energy consumption by sources in 2018 and 2019 is shown in Table 1. Hydroelectric energy data are not given under renewable energy in the reference.

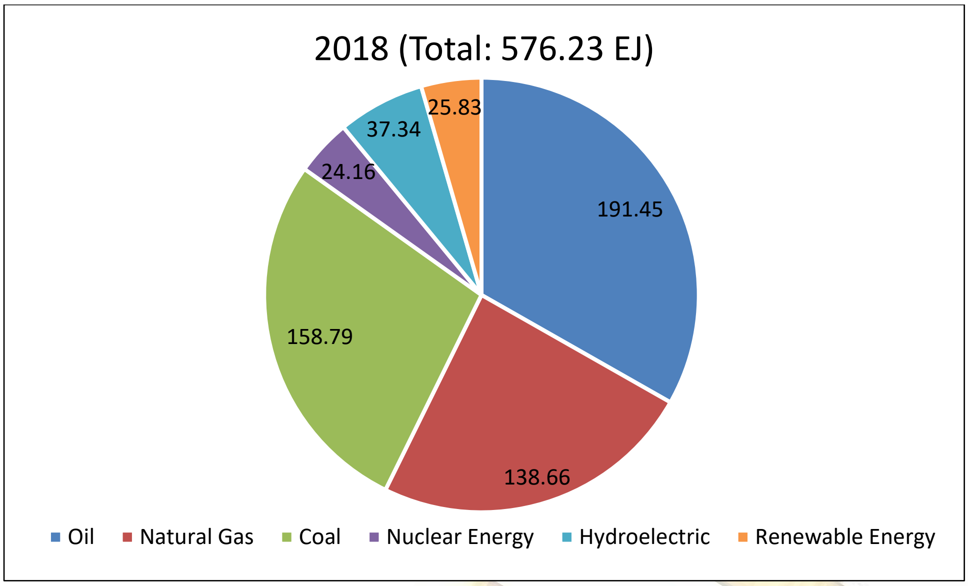

Figure 1. Primary energy consumption in EJ by sources in 2018 (BP, 2020a:9)

Because of the rapid consumption of these resources, renewable energy sources are essential. Besides, as it is known, fossil energy resources cause global warming, leading to various natural disasters. It is crucial to turn to clean, reliable and sustainable renewable energy sources instead of fossil energy resources, which are known to cause significant damage to the environment (Kılıç, 2015:29).

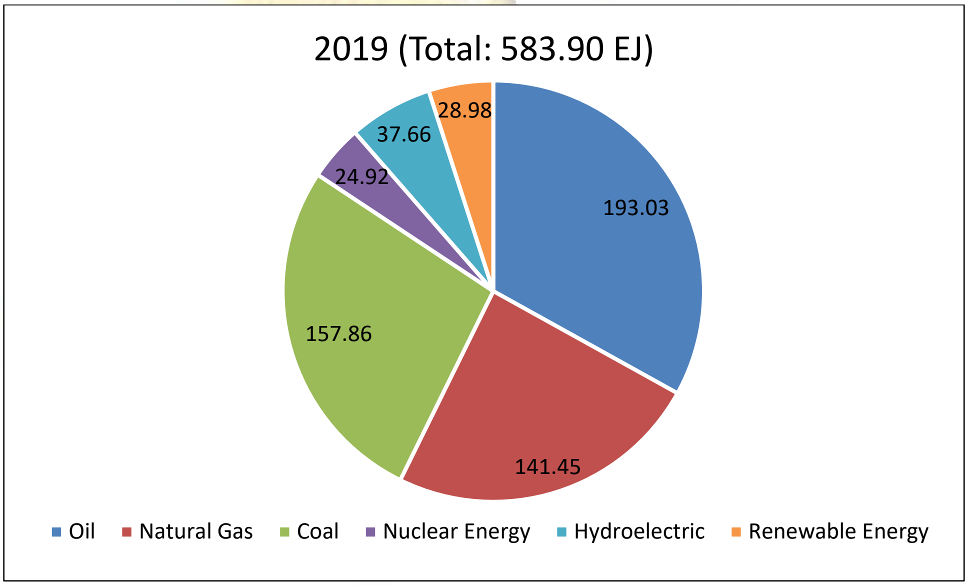

Figure 2. Primary energy consumption in EJ by sources in 2019 (BP, 2020a:9)

Table 1. Turkey's primary energy consumption in EJ by sources in 2018 and 2019 (BP, 2020a:9)

Year	Oil	Natural Gas	Coal	Nuclear Energy	Hydroelectric	Renewable Energy	Total
2018	2.00	1.70	1.71	-	0.54	0.34	6.29
2019	2.03	1.56	1.70	-	0.79	0.41	6.49

In addition to the damage caused by fossil energy resources to the environment, our country is heavily dependent on foreign resources in energy supply. Since the 1980s, imported energy resources have been used to meet energy needs. Moreover, high-cost investments in terms of fossil-based imports have come besides. Thus, dependency on foreign resources in energy supply reached a very high level of 72.4% in 2018. Consequently, the cost to our country was $ 43 billion in 2018 and $ 41.6 billion in 2019 (MMO, 2020). It is clear that this situation creates a vast burden on our country's economy and leads to an increase in the current account deficit.

On the other hand, renewable energy costs are decreasing day by day, thanks to technological developments (KPMG, 2019:3). Furthermore, due to its geographical location, Turkey is highly advantageous in solar and wind energy production (Kayıkcı and Kılıç, 2019:213), and increasing the use of these resources will decrease external dependency. (Ceylan and Başer, 2014:57).

Turkey has a high solar energy potential thanks to its location in the so-called sunbelt (Altuntop and Erdemir, 2013:70). Distribution of Turkey's total solar energy potential by regions and months is shown in Table 2 and Table 3. Table 2 shows the total solar energy potential in kWh/m^2 and sunshine duration hours per year for each region. Table 3 shows the total solar energy potential in kcal/cm^2 and kWh/m^2 and sunshine duration hours per month for Turkey.

Table 2. Distribution of Turkey's Solar Energy Potential by Regions (MMO, 2014:167)

Region	Total Solar Energy (kWh/m²-year)	Sunshine Duration (hour/year)
Southeastern Anatolia	1460	2993
Mediterranean	1390	2956
Eastern Anatolia	1365	2664
Central Anatolia	1314	2628
Aegean	1304	2738
Marmara	1168	2409
Black Sea	1120	1971

Table 3. Distribution of Turkey's Total Solar Energy Potential by Months (MMO, 2014:166)

Months	**Monthly Total Solar Energy**		**Sunshine Duration (hour/month)**
	kcal/cm²-month	**kWh/m²-month**	
January	4.45	51.75	103.0
February	5.44	63.27	115.0
March	8.31	96.65	165.0
April	10.51	122.23	197.0
May	13.23	153.86	273.0
June	14.51	168.75	325.0
July	15.08	175.38	365.0
August	13.62	158.40	343.0
September	10.60	123.28	280.0
October	7.73	89.90	214.0
November	5.23	60.82	157.0
December	4.03	46.87	103.0
Total	112.74	1311.0	2640.0
Average	308.0 kcal/cm²-day	3.6 kWh/m²-day	7.2 hour/day

However, not using this potential effectively causes solar energy not to be counted as a solution alternative to the problems above. Efforts should be made to use solar energy effectively and sustainably in our country (Kılıç, 2015:30).

Generally, photovoltaic (PV) solar power systems and concentrated solar power (CSP) systems are used in electricity generation from solar energy (ETKB, 2020).

Turkey has 6901 solar power plants by the end of 2019, and the cumulative installed solar power is 5996 MW (TEİAŞ, 2019; BP, 2020b:A2). Turkey’s cumulative installed solar power by years is shown in Table 4.

Table 4. Turkey's cumulative installed solar power by years (BP, 2020b:A2)

Years	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Cumulative installed solar power (MW)	5	6	7	12	19	41	250	834	3422	5064	5996

Table 5 shows the distribution of Turkey’s electricity generation in terawatt-hours by energy sources in 2018 and 2019.

Table 5. Electricity generation in Turkey by energy sources (BP:2020a:61)

Year	**Oil**	**Natural Gas**	**Coal**	**Nuclear Energy**	**Hydroelectric**	**Renewable Energy**			**Other**	**Total**
						Wind	**Solar**	**Other**		
2018	0.3	92.5	113.2	-	59.9	19.9	7.8	10.1	1.0	304.8
2019	0.2	58.1	114.6	-	89.2	21.7	10.9	12.7	1.1	308.5

Both Table 4 and Table 5 show that there are developments in the field of solar energy. However, these developments are insufficient. Our country, which has a high potential for solar energy, will reduce its external dependency and remove many uncertainties in the future due to fossil energy resources by increasing installed solar power and using our solar potential better.

Prediction plays a vital role in the field of energy. Various studies in the literature have made predictions using ANN methods. Elizondo, Hoogenboom and McClendon (1994) developed an ANN model to predict daily solar radiation. Mohandes, Rehman and Halawani (1998) estimated global solar radiation using ANNs. Li, Wunsch, O'Hair and Giesselmann (2001) estimated wind turbine energy production using ANNs. Reddy and Ranjan (2003) estimated the average daily and hourly values of global solar radiation using ANNs and compared this with other correlation models. Sözen (2004) mapped Turkey's solar potential using ANNs. Sözen, Arcaklioglu, Ozalp and Caglar (2005) forecasted the solar potential of Turkey with ANNs. Zhou, Wu and Yan (2005) estimated solar radiation using ANNs. Bilgili, Sahin and Yasar (2007) used ANNs to predict wind speed at the target station with reference station data. Ata (2008) analyzed the energy yield of an autonomous wind turbine at different heights using ANNs. Rehman and Mohandes (2008) estimated global solar radiation with ANNs using air temperature and relative humidity. Lam, Wan and Yang (2008) modelled solar radiation with ANNs for different climates of China. Bosch, Lopez and Batlles (2008) estimated daily solar radiation in a mountainous region using ANNs. Mabel and Fernandez (2008) predicted wind power generation. Senkal and Kaleli (2009) estimated solar radiation in Turkey using ANNs and satellite data. Fadare (2009) modelled the solar energy potential in Nigeria using an ANN model. Taşcıkaraoğlu and Uzunoğlu (2011) predicted wind speed by using the wavelet transform (WT) and ANNs. Khatib, Mohamed, Sopian and Mahmoud (2012) predicted solar power generation for Malaysia using ANNs. Mellit, Sağlam and Kalogirou (2013) estimated the energy to be produced by a PV module with an ANN-based model. Kılıç and Arabacı (2015) predicted future wind speed values for Burdur province by using ANN method. Kaya, Caner and Oğuz (2016) determined the wind potential of Kastamonu province by modelling six different wind turbines and using ANNs and adaptive neuro-fuzzy inference systems. Dumitru, Gligor and Enachescu (2016) forecasted photovoltaic energy production using ANNs. Li, Rahman, Vega and Dong (2016) developed a hierarchical approach for forecasting photovoltaic energy production using machine learning methods. Şahan and Yüksel (2016) predicted solar energy using ANNs with meteorological data from the Mediterranean region. Şenol and Musayev (2017) predicted electricity generation from wind energy with ANNs. Filik and Filik (2017) developed a new hybrid approach based on autoregressive and ANNs for prediction of short-term wind speed. Özsoy and Aydogan (2017) used ANNs for predicting installed wind power in Turkey. Şenol (2017) predicted wind energy and wind energy potential using ANNs in his master's thesis. Dumitru and Gligor (2017) forecasted the daily average energy production for wind energy with ANNs. Karasu, Altan, Sarac and Hacioglu (2017) predicted solar radiation with machine learning methods. Çevik, Çakmak and Altaş (2017) made a forecast of hourly solar radiation for Trabzon province a day ahead with the help of ANNs. Köse, Atila, Güneşer and Recebli (2018) developed a new analytical method for estimating hourly and daily wind speed and compared the results with estimates obtained with ANNs. Kırbaş (2018) made a short-term multi-step wind speed prediction using statistical methods and ANNs. Cantürk (2018) predicted electricity from a wind farm with ANNs in his master's thesis. Altınsoy and Bal (2019) used ANNs in long-term wind speed predictions and conducted a performance review. Huang and Kuo (2018) forecasted short-term wind speed with ANNs. Uğuz, Oral and Çağlayan (2019) predicted the energy to be obtained from PV power plants using machine learning methods. Gabralı and Aslan (2020) estimated short and medium-term solar radiation in Istanbul Büyükçekmece District with ANNs.

In this study, cumulative installed solar power was predicted for Turkey with ANN and BLSTM. As far as we reviewed, there is no such study using these two methods in order to predict the cumulative installed solar power for Turkey. It was aimed to assist in energy production planning for the future and guide in the correct direction of energy investments to be made.

2. ARTIFICIAL NEURAL NETWORK

Various prediction methods are used in the literature. In this study, it is aimed to predict the cumulative installed solar power by using ANN and BLSTM. ANNs are an artificial intelligence and machine learning method inspired by biological nerve cells (Esfe, Saedodin, Sina, Afrand and Rostami, 2015:51). ANNs generally consist of an input layer, one or multiple hidden layers, and an output layer, neurons in these layers and weights. Figure 3 shows a network with 24 neurons. This method is used for prediction and classification from existing data. For this purpose, the system is trained with real data and then it is expected to produce outputs suitable for test data. ANN is used for classification and prediction purposes in many areas such as skin cancer level determination (Esteva, Kuprel, Novoa, Ko, Swetter, Blau and Thrun, 2017), detection of automobile engine faults (Ahmed, El Sayed, Gadsden, Tjong and Habibi, 2014), drug classification (Byvatov, Fechner, Sadowski and Schneider, 2003), electric load estimation (Park, El-Sharkawi, Marks, Atlas and Damborg, 1991), stock market forecast (Ticknor, 2013), wind speed estimation (Khosravi, Koury, Machado and Pabon, 2018) and electricity energy demand forecasting (Özden and Öztürk, 2018) because of its adaptability, non-linearity and arbitrary function mapping ability (Garg, Sharma, Parmar, Soni, Singh and Maji, 2016).

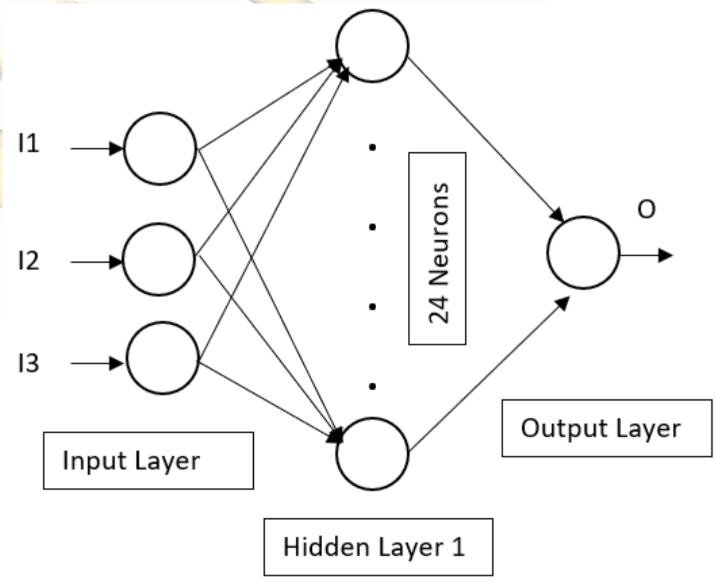

Figure 3. Network in structure 3-24-1

Another popular algorithm inspired by ANNs is deep learning (networks) algorithms. These algorithms are used in many areas such as image processing, classification and natural language processing (Deng and Yu, 2014:202). These methods, which we can call deep learning networks, are different from classical ANNs in various ways, such as layer numbers (LeCun, Bengio and Hinton, 2015:436). Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are the most well-known deep learning algorithms. RNNs can handle input sequences of sequential length and time series problems, but gradient can descend or ascend in the training process (Salamon and Bello, 2017, Bengio, Simard and Frasconi, 1994). This can cause gradient loss issues in training and cause learning problems not to find the correct relationships in the sequences of the RNN model. This is now LSTM which is a particular version of the regular RNN. Employees such as LSTM speech recognition (Hughes and Mierle, 2013), signal works (Yildirim, 2018), text classification (Zhou, Qi, Zheng, Xu, Bao and Xu, 2016), video identification (Bin, Yang, Shen, Xie, Shen and Li, 2018) are used. Normal (One Way) LSTMs can fail in sequential operations such as time series since they do one operation (Graves and Schmidhuber, 2005). For this reason, BLSTMs are a connection and run two LSTMs in the input sequence instead of one LSTM in problems where the input sequence is all time steps (Figure 4). The first LSTM can be made over the input sequence (from past to future) and the second LSTM operates in the opposite direction (from the future to the past) on the copy of the input sequence (Kiperwasser and Goldberg, 2016:316). Thus, it can enable the system to learn the problem faster and more completely.

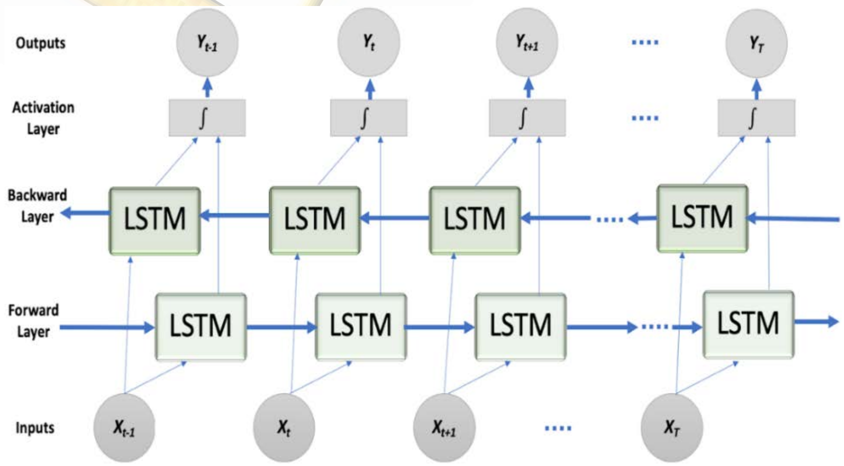

Figure 4. BLSTM structure

3. IMPLEMENTATION

In this study, Turkey's data on cumulative installed solar power given in Table 4 for the period 2009-2019 were used. The data were collected from an online database. Therefore, an Ethics Committee Permission was 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. In order to get good results, the data were transformed into a series with three elements. ANN and BLSTM methods were used on these series, which gives good results in prediction processes. In both methods, the cumulative installed solar power values in megawatts of consecutive years were used as three inputs (I1, I2, I3), and the cumulative installed solar power value of the year after these consecutive years as the only output (O) (Table 6). The values of I1, I2, I3, and O in the first row are the cumulative installed solar power data for the years 2009, 2010, 2011, and 2012 in Table 4, respectively. The second input value in the first row is used as the first input value in the second row. The third input value in the first row is used as the second input value in the second row. The output value in the first row is used as the third input value in the second row. This shifting is continued for the remaining six rows. In other words, the values in the first row are from 2009, 2010, 2011, and 2012, respectively, while those in the second row are 2010, 2011, 2012, and 2013. This process is continued until 2019. The aim here is to produce data series to be applied in the method.

Table 6. Three-element data set of installed solar power values for the period 2009-2019

I1	I2	I3	O
5	6	7	12
6	7	12	19
7	12	19	41
12	19	41	250
19	41	250	834
41	250	834	3422
250	834	3422	5064
834	3422	5064	5996

The ANN method includes three inputs, one output and one hidden layer (3-24-1) with 24 neurons. It was carried out with 200 epochs during ANN training, and from the data for the years 2016, 2017 and 2018, a value of 5995.989 was estimated for the actual value 5996. A relative error has been found -0.0002% after comparing both values (Table 7).

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, 2014:1, Ruder, 2016:7).

By this method, a value of 6146.651 was estimated for the actual value 5996 for 2019. A relative error has been found 2.5125% after comparing both values (Table 7).

Table 7. Prediction for 2019 from the data for the period 2016-2018

Methodology	2016	2017	2018	2019
Actual values in MW	834	3422	5064	5996
ANN Prediction in MW (Relative Error -0.0002%)				5995.989
Bidirectional LSTM Prediction in MW (Relative Error 2.5125%)				6146.651

Moreover, the ANN method is implemented on the data for the period 2016-2018 in order to predict the cumulative installed solar power value for 2019 with different network structures. As shown in Table 8, the best prediction value is obtained by the 3-24-1 network structure.

Table 8. Prediction for 2019 with different network structures

Network Structure	**Prediction in MW**	**Relative Error %**
3-5-3-1	6009.53	0.2257
3-5-5-1	5627.861	-6.1397
3-3-5-1	5876.123	-1.9993
3-10-5-1	5805.749	-3.1730
3-5-10-1	5601.440	-6.5804
3-5-1	5674.155	-5.3677
3-8-1	5992.897	-0.0518
3-11-1	5995.281	-0.0120
3-14-1	5995.632	-0.0061
3-17-1	5995.931	-0.0012
3-20-1	5995.930	-0.0012
3-24-1	5995.989	-0.0002

ANN and BLSTM methods were used to estimate the value for 2020 from the data for 2017, 2018, and 2019 with the same training and optimization parameters. The cumulative installed solar power value was predicted as 6499.992 for the year 2020 by the ANN method and as 6617.015 by the BLSTM method (Table 9). Although the actual value for 2020 is unknown, the cumulative installed solar power is 6294.7 MW by the end of August 2020 (TEİAŞ, 2020).

Table 9. Prediction for 2020 from the data for the period 2017-2019

Year	2017	2018	2019	2020
Actual Value	3422	5064	5996	-
ANN Prediction				6499.992
BLSTM Prediction				6617.015

Furthermore, the ANN method is implemented on the data for the period 2017-2019 in order to predict the cumulative installed solar power value for 2020 with different network structures. The results are given in Table 10.

Table 10. Prediction for 2020 with different network structures

Network Structure	Prediction in MW
3-5-5-1	6341.412
3-3-5-1	6442.569
3-10-5-1	6367.772
3-5-10-1	6356.365
3-5-1	6230.179
3-8-1	6375.942
3-11-1	6499.175
3-14-1	6499.123
3-17-1	6499.834
3-20-1	6499.925
3-24-1	6499.992

In order to compare the results of the ANN and BLSTM methods, other prediction methods such as Support Vector Regression (SVR), Decision Tree Regression (DTR) and Random Forest Regression (RFR) are implemented on the same data with optimized parameters in order to predict the cumulative installed solar power value for 2020 (Table 11).

Table 11. Comparison of the results obtained from ANN and BLSTM methods with the results of other prediction methods

Prediction Method	Prediction for 2019 (Actual value is 5996 MW)	Prediction for 2020 (Actual value is unknown)
ANN	5995.989	6499.992
BLSTM	6146.651	6617.015
SVR	2945.31	3429.96
DTR	5064	5996
RFR	4336.26	5490.98

As shown in Table 11, the ANN method yielded the best prediction result for 2019 when compared with other prediction methods. Since the value for 2020 is unknown, it can not be determined which method gives the best result.

4. CONCLUSION

In this study, the cumulative installed solar power was predicted for 2020 by using ANN and BLSTM. The results show that the ANN method yields a better result than the BLSTM method for 2019. The predicted value for 2020 may not be reached due to the pandemic, as the pandemic has negatively impacted energy investments in every field. Investments in solar energy in Turkey are expected to increase with the decline in the impact of the pandemic. Turkey has great potential in solar energy. Considering this potential, it should be aimed to produce their own energy in uncultivated land, on house and company roofs that are exposed to the sun.

In future research, by considering the solar power capacity and the capacity of other renewable energy sources in Turkey, their contributions to the national economy can be analyzed financially by years, and the contribution of solar energy to the economy can be estimated over the years with the machine learning methods.

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