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FORECASTING TURKEY ELECTRICITY CONSUMPTION WITH DEEP LEARNING BI-LSTM MODEL

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Research Article

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ABSTRACT

The energy consumption of Turkey, which is among the developing countries, is constantly increasing. Despite this increasing energy need, it is an insufficient country in terms of energy production. Turkey, which is a foreign-dependent country in energy use, has problems with sustainable energy supply. Especially recently, Russia's restrictions on energy exports to European countries have caused an energy crisis all over the world. For this reason, energy supply security has a vital role for Turkey as well as for the rest of the world. In this context, the estimation of energy consumption for future periods is a strategic issue that should be emphasized. In the study, monthly energy consumption amounts of Turkey between January 2005 and November 2018 were taken and a five-year estimate of the ever-increasing electricity consumption in the range of 2019-2023 was made using bi-directional LSTM (Long Short Term Memory) models (ADAM, RmsProp, SGDM). The highest performance in the models was obtained with RMSprop optimization. The monthly electrical energy consumption data between 2019-2020 and the estimated data of monthly electricity consumption for the same period obtained by RMSprop optimization were compared. According to the optimization result, Turkey's electricity consumption will continue to increase. Turkey should put into effect the necessary plans quickly in the face of this increasing need. Incorporating the education of households into plans for energy conservation may be a viable solution.

Key Words: *Bi-LSTM, Deep Learning, Electricity Consumption Forcast, Energy Economics, Energy Demand*

TÜRKİYE ELEKTRİK TÜKETİMİNİN DEEP LEARNING BI-LSTM METODU İLE TAHMİNİ

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ÖZ

Gelişmekte olan ülkeler arasında yer alan Türkiye'nin enerji tüketimi sürekli artış göstermektedir. Artan bu enerji ihtiyacına rağmen enerji üretme konusunda ise yetersiz bir ülkedir. Enerji kullanımında dışa bağımlı bir ülke konumunda olan Türkiye, sürdürülebilir enerji arzında problemler yaşamaktadır. Özellikle son dönemde Rusya'nın Avrupa ülkelerine enerji ihracatında kısıtlamalara gitmesi tüm dünyada enerji krizine neden olmaktadır. Bu nedenle tüm dünyada olduğu gibi Türkiye için de enerji arz güvenliği hayati bir role sahiptir. Bu bağlamda gelecek dönemlere ait enerji tüketim tahmini, üzerinde durulması gereken stratejik bir konudur. Çalışmada Türkiye'nin 2005 Ocak-2018 Kasım yılları arasındaki aylık enerji tüketim miktarları alınmış ve sürekli artan bir grafik seyreden elektrik tüketiminin bi-directional LSTM modelleri (ADAM, RmsProp, SGDM) ile 2019-2023 aralığında 5 yıllık tahmini yapılmıştır. Modellerde en yüksek performans RMSprop optimizasyonu ile elde edilmiştir. 2019-2020 yılları arasında aylık gerçekleşen elektrik enerjisi tüketimi verileri ile RMSprop optimizasyonu ile elde edilen aynı dönem için aylık elektrik tüketiminin tahmini verileri karşılaştırılmıştır. Optimizasyon sonucuna göre Türkiye elektrik tüketimi artmaya devam edecektir. Türkiye artacak bu ihtiyacı karşısında gerekli planlamaları hızlı bir şekilde yürürlüğe koymalıdır. Enerji tasarrufu için hane halklarının eğitiminin planlara dahil edilmesi uygun bir çözüm olabilir.

* Genişletilmiş olarak "Turkish energy sector strategic position and neural network prediction of energy consumption models with" başlıklı tezden türetilmiştir.

Anahtar Kelimeler: *Bi-LSTM, Deep Learning, Elektrik Tüketim Tahmini, Enerji Ekonomisi, Enerji Talebi*

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Introduction

With the loss of clarity of the borders between countries and the rapid increase in industrialization, an increase is observed in global energy consumption. In recent years, there has been a rapid increase in energy consumption worldwide, with a strong boom from 8,588.9 million tons of oil equivalent (Mtoe) in 1995 to 14,2011 Mtoe in 2021 (Dong et al., 2020; Total Energy Consumption… https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html) As in hydrocarbon-based energy, electricity consumption, which is a secondary energy source, shows an increasing trend in the same parallel.

The fact that the energy reserves are not evenly distributed in the world may cause conflicts as well as cooperation between countries. As the main issue, energy is a reason for both international war and indirect sanctions on other countries. The recent Russia-Ukraine war is the most up-to-date example of this issue. The tension between Europe and Russia has caused Russia to restrict its energy exports to Europe. This brought about an energy crisis in Europe. Such a conjuncture is also an indication of the increasing importance of energy.

In addition to the increasing demand, problems arise from the storage of electrical energy and it can be difficult to control the energy demand. For this reason, the production, transmission, and consumption of electricity, which is constantly needed, is a key role in terms of management. To determine the most appropriate strategies for the current situation, being able to accurately predict how the consumption values will occur in the future is an issue that needs to be addressed. In this context, in addition to the views of the actors in the sector, the methods to be developed for consumption forecasting play a vital role in both macro and micro scales.

Literature

The need for accurate forecasts is clear given that energy distribution infrastructure is improving capabilities, undergoing rapid transformation, and predicting faster response times regarding energy resource allocation flexibility. This can bring many benefits, such as increases in production costs, and realistic energy price estimations (Koukaras., 2021). Increased forecast accuracy facilitates the elimination of energy imbalances between production and consumption. For this reason, it is important from a managerial point of view to use the highest performance forecasting models.

In the literature, There are many studies on the prediction of energy consumption (Ahmad et al., 2020; Anand and Suganthi, 2020; Li et al., 2011) and production (Fara et al., 2021; Gandelli et al., 2014; Pazikadin et al., 2021; Zhang et al., 2021). It can be seen in studies that ANN models perform higher than other models. In this context, to achieve high performance, the monthly electrical energy consumption of Turkey has been tried to be estimated with artificial neural network models.

Considering the past periods of Turkey, it can be seen in Figure 1 that electrical energy consumption has been increasing rapidly every year.

The net consumption value, which was 59237 GWh in 1993, increased to 262702.1 GWh in 2020. Consumption has increased by approximately 345 percent in 19 years (Figure 1).

As can be seen in Table 1, licensed and unlicensed total installed capacity in Turkey was 99 820 MWe as of 2021 and increased by 4.1 percent compared to 2020. The increase in the production value is 9.4 per thousand as of the same year. The number of electrical energy users increased by 2.68 percent and reached 47 3011 976. Actual consumption increased by 8.13 percent and reached 329 634 GWh. Imported electricity increased by 23.34 percent (2329 GWh), while 4 187 GWh was exported with an increase of 68.56 percent. While Turkey imported electrical energy from Bulgaria (1689,5 GWh), Georgia (169.9 GWh), and Greece (30.1 GWh) in 2020; exported to Greece (1841.1 GWh), Bulgaria (326 GWh), Georgia (315 GWh), and Syria (1.6 GWh) (TEİAŞ, 2022).

Electricity imports, which increased rapidly between 2010 and 2014, started to decrease after 2014 (Figure 2). In this process, electricity exports followed a fluctuating graphic and increased by 1.7 times in 2021 compared to the previous year.

The total installed capacity in Turkey increased by 12.8 percent in 2021 compared to 2018 (Table 2). The largest part of the total installed capacity in 2021 is hydraulic energy (31.5%). The second largest share belongs to natural gas (26%). The highest increase compared to 2018 based on resources is biomass (145.4%). Solar (53.3%) and wind (51.7%) are also the highest increase. The capacity decrease in the installed capacity is seen only in Fuel-Oil (-64.5%)

In Turkey, electricity production increased by 9 percent in 2021 compared to 2018 (Table 3). The highest increase in parallel to the installed capacity is seen in biomass electricity generation with 121 percent. There is also an increase in production caused by solar (61.2%), and wind (56.2%). The highest decrease in production is seen in diesel (-64.4%), while other electricity production resources have imported coal (-12.9%), lignite (-3.7%), and hydraulic (-7,1) decreases.

In Figure 3, the production rates of Turkey's electrical energy from imported and domestic sources can be seen. Until 2018, the share of imported resources is over 50 percent. However, the rate of electricity production from domestic sources increased to 61.2% in 2019, thus the share of imported sources decreased rapidly. The rate of electrical energy produced from imported sources in 2020 is 43.6%.

Artificial Neural Networks

Artificial neural networks (ANN), in which nerve cells or neurons are the basic processing element of the central nervous system, it is aimed to understand the human brain and imitate its power (Fauset, 1994.). Artificial neural networks, which are frequently encountered in the literature, can perform a surprising number of tasks very efficiently. Thanks to this feature, artificial neural networks developed by imitating the information-processing process of the brain become a powerful computing device, that can learn from examples and generalize to examples that have never been seen before (Zhang et al, 1998.). A neural network consists of simple processing units and tends to accumulate and memorize the information that the network experiences. It acts as an intensely parallel distributed processor to ensure that the data it learns is used. Artificial neural networks are similar to the brain in two aspects. The first of these; obtains information through learning, while the other neurons (nerve cells) are used to store information (Haykin: 1998).

Although the neural network is very simple, it gives the ability to solve many more problems than can be solved by a network with only one input and output unit, together with a non-linear activation function of a hidden unit. Another advantage is that they can be preferred in time series estimation problems due to their flexible modeling capability. Since a certain linear or curvilinear model pattern does not need preconditions such as normal distribution and stationarity, ANN can be applied to any time series. On the other hand, training a network with hidden units can be difficult due to problems such as finding the most appropriate values for the weights (Fauset, 1994; Erilli et al., 2010.). In artificial neural networks, which consist of connecting cells to each other in various ways, cell outputs can be connected to other cells or themselves as inputs via weights. Various ANN models have been developed according to the connection types of cells, learning styles, and activation functions used. The first ANN architectures are single-layer (Figure 4) and multi-layer (Figure 5) models. In the simplest form, a layered network has a structure in which signals flow directly from the input layer to the output layer. This flow cannot be in the opposite direction. In other words, this network is strictly forward-looking. (Haykin, 1998.).

A recurrent neural network distinguishes itself from a forward neural network by having at least one feedback loop. For example, a recurrent network may consist of a single layer of neurons feeding each neuron's output signal back to the inputs of all other neurons. There is no self-feedback loop in the network, and self-feedback is when the output of a neuron is fed back to its input (Figure 6) (Haykin, 1998.).

Other recurrent network models (RNN) that do not get hit by the optimization barriers that exist in simple recurrent networks (SRNs) and are used to develop cutting-edge technology in many difficult problems are “Long-Short-Term Memory (LSTM)” and LSTM's b3idirectional (forward and backward) extension is “bidirectional-LSTM” architectures (Figure 7) (Gref vd., 2017).

SGDM (Stochastic Gradient Descent with Momentum): The stochastic gradient descent algorithm can oscillate along the path of the steepest descent towards the optimum. Adding a momentum term to the parameter update is one way to reduce this oscillation (Murphy, 2012). The stochastic gradient descent with momentum (SGDM) update is;

$$\theta_{\ell+1} = \theta_{\ell} - \alpha \nabla \mathrm{E}(\theta_{\ell}) + \gamma(\theta_{\ell} - \theta_{\ell-1})$$

Where γ determines the contribution of the previous gradient step to the current iteration. To train a neural network using the stochastic gradient descent with momentum algorithm, specify Training Algorithm as SGDM. To specify the initial value of the learning rate α, use the 'Initial Learn Rate'.

RMSprop (Root Mean Square Error Probability): RMSprop is an adaptive learning method proposed by Geoff Hinton. RMSprop divides the learning rate by the mean of the exponentially decreasing square gradients. The operation function is as follows (Ruder, 2017);

$$E[g^2]_t = 0.9E[g^2]_{t-1} + 0.1g_t^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} g_t$$

Hinton recommends taking γ as 0.9, and η taking 0.001 for the learning rate.

ADAM (Adaptive Momentum Estimation): The optimization calculates individual adaptive learning rates for different parameters by estimating primary and secondary gradients. In the rescaling of the gradient, the invariance of the size of the parameters, the limitation of the step sizes, the fact that it does not require a stationary purpose, and that it can work with intermittent gradients are among the advantages of ADAM (Kingma & Ba, 2015). The performance function is as follows (Yazan & Talu 2017);

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\acute{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\tilde{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\tilde{v}_t} + \epsilon} \cdot \acute{m}_t$$

Optimization takes advantage of RMSprop, but while RMSprop performs a momentum as a parameter update on the scaled gradient, in ADAM, parameter updates are performed using the average of the first and second moments of the gradient (Kingma, Ba 2015).

Methodology

In the study, a bi-LSTM RNN time series model was created by using 167-month electricity consumption data for the periods between January 2005 and November 2018 provided by The Turkish Electricity Transmission Corporation. Since time series analysis is preferred with the single input method, monthly electricity consumption values are taken into the system as input. According to the models created, the monthly estimated values, and the actual values between 2019-2021 were compared. In the created bi-LSTM architecture, “ADAM”, “SGDM” and “RMSProp” optimization algorithms are used to achieve the highest performance. For each optimization type, the number of layers and units were tried separately, normalization and standardization were used separately, and 75% and 80% of training were carried out for each layer and unit separately as validation. To avoid the overfitting problem, a dropout layer is used in the architecture. Matlab 2019a program was used in the study.

Findings

A total of 886 trainings were tried and the best values were obtained in the "RMSProp" optimization as seen in Table 4. The best preprocess inputs for all optimizations are 80% validation and a standardized normalization method. In the RMSProp optimization model, where the highest performance is obtained, Corr= 98.633%, R2= 96.66% and MSE=0.029407. In a single-layer architecture, the unit value is 100. The training results of the obtained model can be seen in Figure 8 and Figure 9.

In figure 8, the y-axis shows the electricity consumption values and the x-axis shows the months. Targets (blue line) show actual values while outputs (orange line) show estimated values. With 80% validation, the left side of the dashed line is the training zone and the right side is the testing zone. In the training part, a 96.58% similarity was achieved. In the testing part, this rate is slightly reduced (R2 =73,4%) (Figure 9). Increasing the length of the dataset may give better results for testing.

As a result of the standardized RMSprop optimization model, the estimated electricity consumption values for the next 60 months and the actual electricity consumption values in 2018 can be seen in Table 5.

It is known from the values realized in 2005-2018 that electricity consumption reached the highest consumption value in the summer months. Although the model can predict the consumption periods for about 30 months well, it is observed that the high values shift to the spring months in the 3rd year. For this reason, it can be seen that the model weakens in predicting the distant future. Since it shows a non-linear trend, this difference is felt more dominantly.

The chart of the 2005 and 2023 electricity consumption values of the RMSprop optimization model created can be seen in Figure 10.

In Figure 11, there are monthly consumption forecast data for the years 2019-2020 obtained by RMSprop optimization using monthly electricity consumption values between 2005-2018. In addition, the electricity consumption values realized in Turkey for this period are also included in the chart.

Result And Discussion

Among the models obtained for electricity consumption estimation, the RMSprop optimization model, which was applied standardization preprocess and operated with an 80% training rate, showed the highest performance. The electricity consumption, which reached the maximum values in the summer months, showed a high consistency for about 30 months in the RMSprop projection and showed the maximum value in the summer months, while it shifted for the next and showed the maximum value in the spring months. It can be said that the prediction model shows weakness as it moves away from real-time. This is a problem that can be encountered frequently in projections. For this reason, it is necessary to keep the data set longer as input to maximize the periodic consistency. If the data set cannot be kept long, it can be stated that the future forecast values of 24-30 months for a 167-month data set will be correct in terms of developing managerial strategies. According to the model obtained, it can be observed that electricity consumption will increase over the years. Constantly increasing electricity consumption is an expected situation for Turkey, which is a developing country. However, Turkey, which is poor in energy production, should manage this situation in the best way. Because electricity, which is a secondary energy source, directly affects primary energy sources and is affected by them. The values estimated by the RMSprop optimization between 2019 and 2020 and the electricity consumption values realized in Turkey can be seen in Figure 11. Electricity consumption, which followed a different trend in the March-July 2020 range, is linked to Covid-19. With the onset of the epidemic, the disruption of working life in public and private institutions in March 2020 caused a rapid decrease in electricity consumption. As of June 2020, with the introduction of flexible working hours and the start of the summer period, a rapid increase in consumption can be seen again. In August 2020, the highest value (292968.4 GWh) was reached for the 2-year pre- and post-pandemic period. If the pandemic does not occur, we predict that the values we predict with artificial neural networks will form a trend closer to the actual values. Turkey has recently made a breakthrough in expanding its renewable energy resources capacity (Table 2). Turning to their resources in energy production is among the most important strategies to be developed for countries. The energy crisis caused by the war between Russia and Ukraine has a great impact that can affect all sectors of the world. The biggest source of electricity production in Turkey is natural gas (32.7% share of natural gas in 2021 - Table 3). With the decrease in the amount of precipitation brought by global warming, the share of hydraulic production has been decreasing over the years. Considering the magnitude of the impact of natural gas, the Russia-Ukraine crisis, and global warming, it is important to increase solar, wind, and biomass capacity. Considering the size of energy imports, electricity produced from renewable energy sources is a method that will relieve Turkey in terms of sustainable energy. However, the fact that the nuclear energy source has come to the fore in the country is an important development in this respect. Nuclear energy, which is preferred by the most important electricity exporters, emerges as a method that should be used for Turkey. The fact that renewable energy is not a guaranteed source periodically can also show that nuclear energy is a preferred method. Considering the importance of the natural gas resource, the Levant basin of the Eastern Mediterranean is in a very important position indirectly in terms of electricity consumption. The management of the hydrocarbon reserves estimated to exist in the Levant basin by Turkey is of vital importance and the region can be the most important source of electricity consumption, which is expected to increase continuously. In addition, raising awareness of the people of Turkey not only on electricity consumption but also on the use of other energy sources that have a share in electricity generation and preventing the illegal use of electricity would be right strategies.

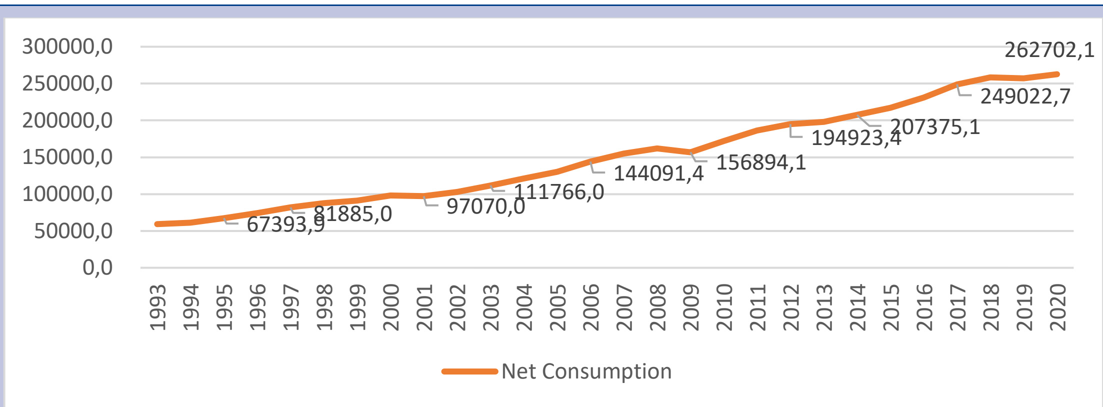


Figure 1. Turkey's Net Electricity Energy Consumption (GWh)   Resource: TEİAŞ, 2022.

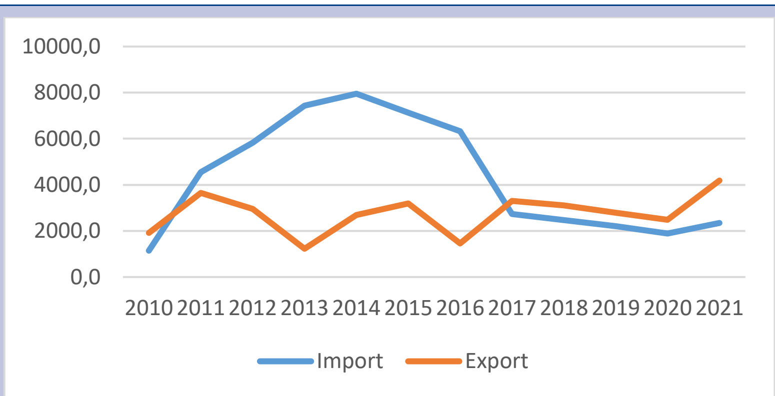


Figure 2. Import and Export of Electricity in Turkey (2010-2021)   Resource: TEİAŞ, 2022.

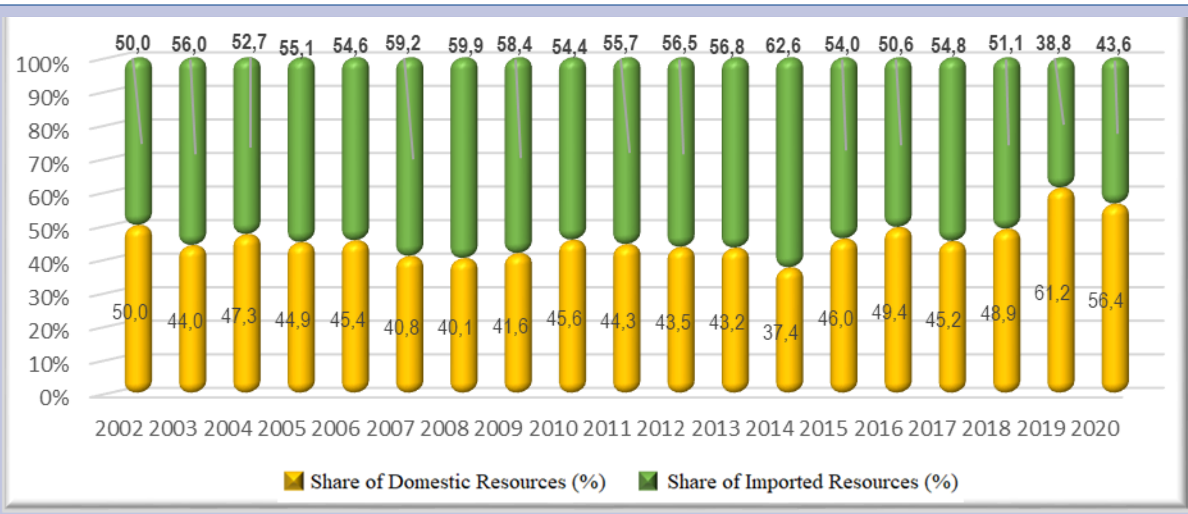
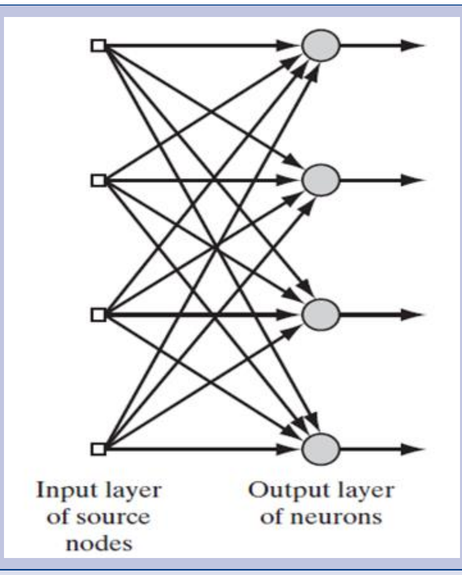


Figure 3. The Share of Domestic and Imported Electrical Energy Production in Turkey Total Production (2002-2020) Resource: TEİAŞ, 2022.



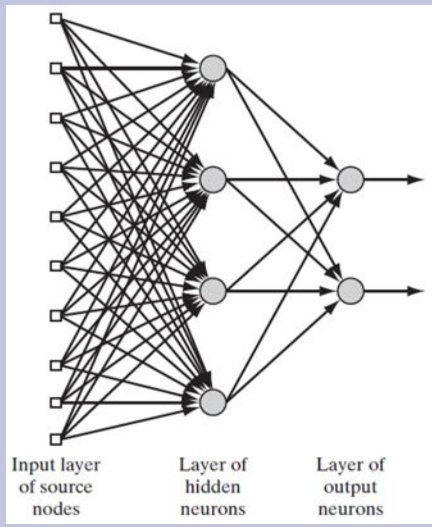


Figure 4. Single-Layer ANN

Figure 5. Multi-Layer ANN

Resource: Simon Haykin, 1998

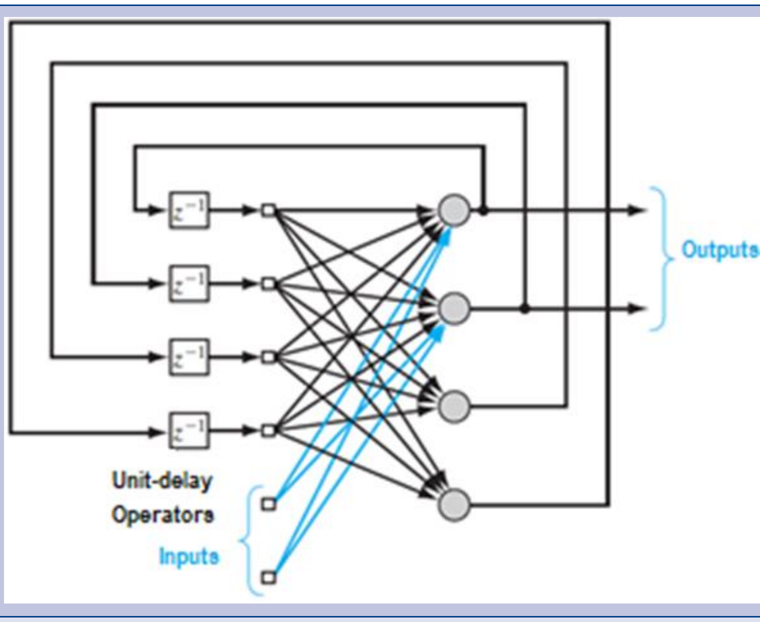


Figure 6. Recurrent Network with Hidden Neurons Resource: Simon Haykin, 1998

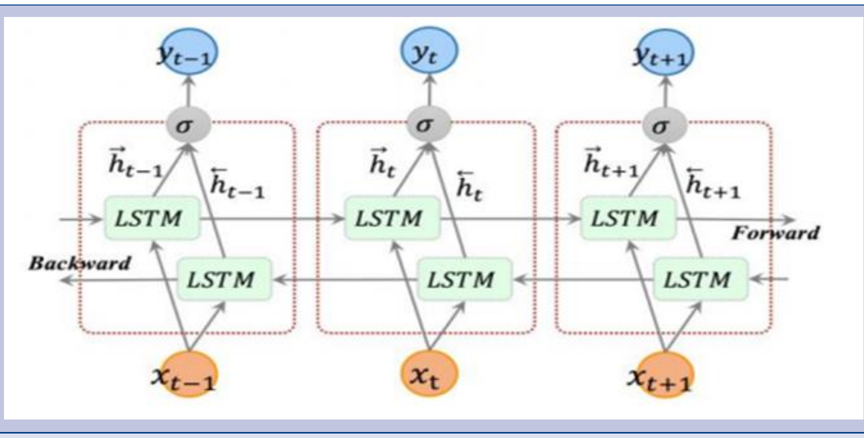


Figure 7. Unfolded Architecture of Bidirectional LSTM with Three Consecutive Step Resource: Chui vd., 2017.

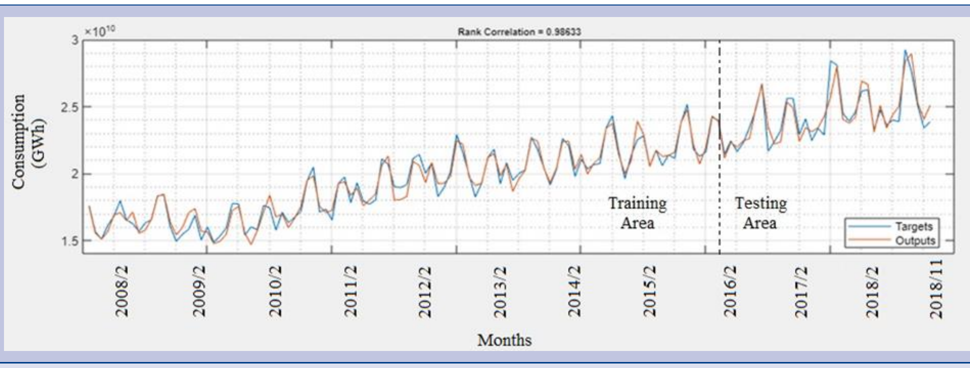


Figure 8. Graph of actual electricity consumption and estimated values obtained by RMSprop optimization

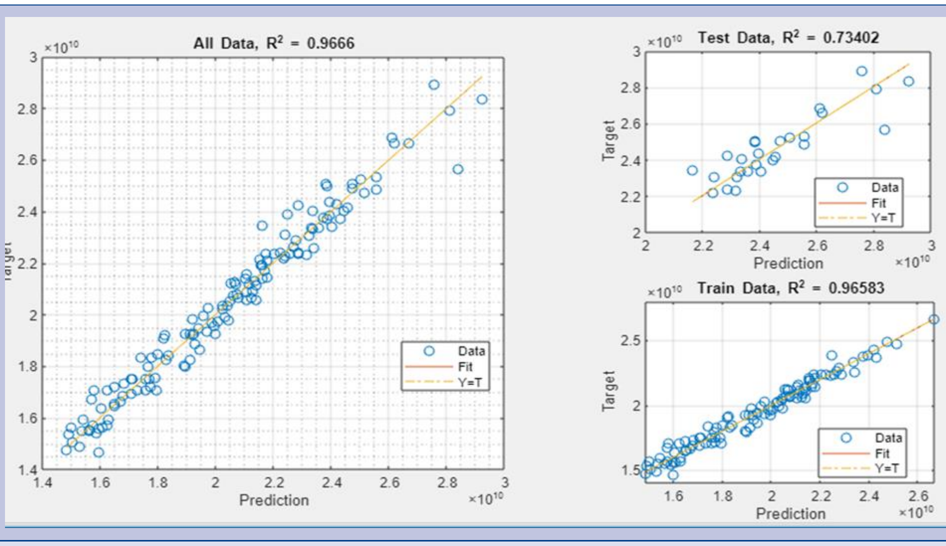


Figure 9. Training and testing chart obtained by RMSprop

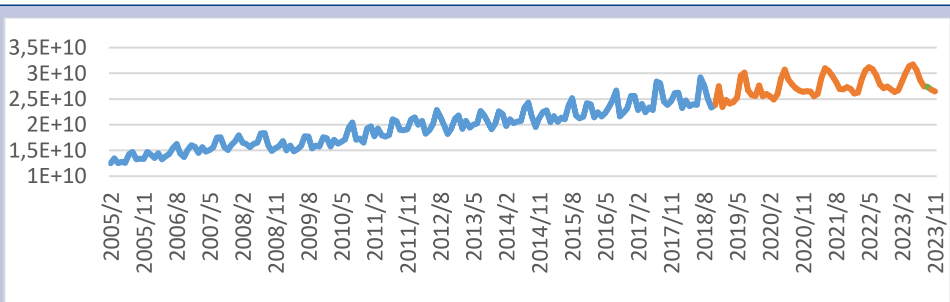


Figure 10. Electricity consumption chart obtained by RMSprop Prediction (2005-2023)

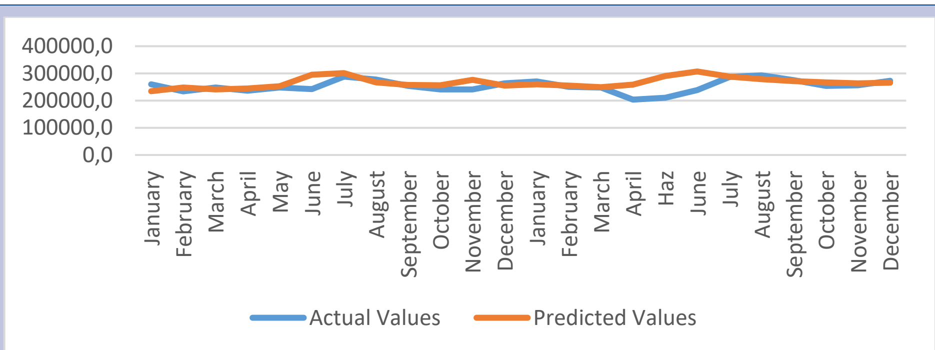


Figure 11. Actual and estimated (by RMSprop) electricity consumption values (2019-2020)

Table 1 *Turkey Electricity Market Overview (2019-2021)*

Parameters	Unit	2019	2020	2021	Change*
Installed Capacity	MWe	91.269	95.890	99.820	4,1
Generation	GWh	76.962,338	73.776,311	74.475,520	0,94
Actual Consumption	GWh	301.983	304.836	329.634	8,13
Number of Consumers	Number	44.958.924	46.077.742	47.311.976	2,68
Import	GWh	2.212	1.888	2.329	23,34
Export	GWh	2.789	2.484	4.187	68,56

** Shows the percentage change between 2020 and 2021.* ***Resource:*** *EPDK, 2021*

Table 2 *Total Installed Capacity by Resources in Turkey (2018-2021)*

Resource Type	2018 Installed Capacity (MW)	2019 Installed Capacity (MW)	2020 Installed Capacity (MW)	2021 Installed Capacity (MW)	Share (%-2021)	Change (2018-2021)
Natural Gas	25885,0	26264,1	26041,9	25964,6	26,0	0,3
Hydraulic	28292,6	28503,0	30983,9	31492,6	31,5	11,3
Lignite	9597,1	10101,0	10119,9	10119,9	10,1	5,4
Import Coal	8938,9	8966,9	8986,9	8993,8	9,0	0,6
Wind	6994,2	7591,2	8832,4	10607,0	10,6	51,7
Geothermal	1282,5	1514,7	1613,2	1676,2	1,7	30,7
Hard Coal	616,2	810,8	810,8	840,8	0,8	36,5
Biomass	670,1	801,6	1115,6	1644,5	1,6	145,4
Asphaltite	405,0	405,0	405,0	405,0	0,4	0,0
Fuel-oil	709,2	305,9	305,9	251,9	0,3	-64,5
Solar	5098,7	5995,2	6667,4	7815,6	7,8	53,3
Naphta	4,7	4,7	4,7	4,7	0,0	0,0
LNG	2,0	2,0	2,0	2,0	0,0	0,0
Diesel	1,0	1,0	1,0	1,0	0,0	0,0
Total	88497,1	91267,0	95890,6	99819,6	100,0	12,8

Resource: *EPDK, 2019; 2020;2021*

Table 3 *Total Electricity Production by Resources in Turkey (2018-2021)*

Resource Type	2018 Total Production (GWh)	2019 Total Production (GWh)	2020 Total Production (GWh)	2021 Total Production (GWh)	Share (%-2021)	Change 2018-2021
Natural Gas	91639,1	56522,7	69277,5	108438,7	32,7	18,3
Hydraulic	59936,8	88884,6	78115,0	55695,2	16,8	-7,1
Lignite	45087,0	46893,7	38163,9	43400,4	13,1	-3,7
Import Coal	62988,5	60381,3	62466,5	54888,8	16,6	-12,9
Wind	19938,5	21749,8	24680,8	31137,4	9,4	56,2
Geothermal	7431,0	8929,7	9929,4	10770,9	3,2	44,9
Hard Coal	2844,6	3518,9	3415,8	3539,8	1,1	24,4
Biomass	3446,9	4521,8	5501,9	7616,6	2,3	121,0
Asphaltite	2328,5	2324,0	2222,9	2373,0	0,7	1,9
Fuel-oil	328,9	732,9	313,0	336,6	0,1	2,4
Solar	8246,4	9620,3	11242,5	13294,3	4,0	61,2
Naphta	0,0	0,0	0,0	0,0	0,0	0,0
LNG	0,0	0,0	0,0	0,0	0,0	0,0
Diesel	0,2	1,0	1,0	0,1	0,0	-64,4
Total	304216,5	304080,8	305330,2	331491,9	100,0	9,0

Resource: *EPDK, 2019; 2020; 2021.*

Table 4 *Parameters with the Highest Performance for Each Optimization*

Parameters	ADAM	RMSprop	SGDM
Correlation	0.98443	0.98633	0.97234
Nmse	0.030426	0.029407	0.043488
R^2	0.96324	0.9666	0.91315
Layer	1	1	1
Unit	75	100	75
Preprocessing	Stand	Stand	Stand
Validation	75	80	80

Table 5 *Future estimated values of electricity consumption (GWh)*

MONTH	2018	2019	2020	2021	2022	2023
JANUARY	262117,3	234575,8	259939,6	264663,6	260754,1	267072,3
FEBRUARY	232308,7	248074,2	255260,4	255344,8	262640,9	283686,5
MARCH	247291,3	241094,0	249035,6	260098,5	287945,6	300574,6
APRİL	235865,4	244254,4	259225,5	290760,3	305581,0	313956,2
MAY	239646,8	252760,0	289976,8	309910,6	311889,6	317265,9
JUNE	238556,6	295104,2	307135,2	304731,0	308130,8	306321,9
JULY	292156,7	301368,6	287985,5	295086,4	295866,9	286438,4
AUGUST	275712,8	266619,8	278598,9	283517,5	278107,2	274777,9
SEPTEMBER	250519,6	257680,4	271182,8	269444,2	271201,3	273662,6
OCTOBER	233758,0	255886,2	266519,1	269005,1	274222,8	268257,9
NOVEMBER	238487,0	276435,4	264057,8	273133,8	268971,3	264875,2
DECEMBER	274914,1	255650,3	265267,1	269585,4	263575,4	

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