Turkish Journal of Electrical Engineering and Computer Sciences

Volume 29 | Number 1 Article 6

1-1-2021

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HARUN ÖZBAY

ADEM DALCALI

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Available at: https://journals.tubitak.gov.tr/elektrik/vol29/iss1/6

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Turkish Journal of Electrical Engineering & Computer Sciences

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Research Article

Turk J Elec Eng & Comp Sci
(2021) 29: 78 – 97
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doi:10.3906/elk-2006-29

Effects of COVID-19 on electric energy consumption in Turkey and ANN-based short-term forecasting

Harun ÖZBAY*, Adem DALCALI
Department of Electrical Engineering, Faculty of Engineering and Natural Sciences,
Bandırma Onyedi Eylül University, Balıkesir, Turkey

Received: 05.06.2020 • **Accepted/Published Online:** 10.09.2020 • **Final Version:** 27.01.2021

Abstract: Due to the coronavirus, millions of people worldwide carry out their work, education, shopping, culture, and entertainment activities from their homes now using the advantages of today's technology. Apart from this, patient care and follow-up are carried out with the help of electronic equipment especially in the institutions where health services are provided. It is important to provide a reliable electricity supply for humanity so that people can perform all these services. In this study, the outlook of energy in Turkey was examined. The current energy consumption and investments were examined. Then, the precautions by the government in the pandemic period according to the occurrence and spread of COVID-19 in the country are given in chronological order. The actual electricity consumption data were obtained daily across the country, after all these precautions. It was observed that electricity consumption decreased significantly, especially on restricted days. It is inarguable that energy consumption estimation should be made in the short term so that the energy sector is not adversely affected by this situation. In this study, more accurate short-term consumption forecasting methods were developed during the COVID-19 pandemic period: nonlinear autoregressive (NARX) and long short-term memory (LSTM) artificial neural networks (ANNs). Between January and April 2019 electrical consumption data were used to train and validate the forecast prediction. The NARX and LSTM are potential candidates for effective forecasting of electricity consumption. However, the obtained LSTM results suggest that the proposed method performs better than the NARX ANN.

Key words: Artificial neural networks, COVID-19, energy consumption, forecasting, long short-term memory

1. Introduction

Turkey has a dynamic economy and rapid population growth. In Turkey, parallel with the economic development, the energy demand is growing. Especially with the increase of purchasing power, electrical appliances used in the houses, small- and medium-sized businesses, and production means that energy is used much more. Therefore, it is highly important to develop efficient energy applications and technologies. Moreover, the usage and development of renewable energy are very important in terms of an increase in energy diversity. From this point of view, it is seen that Turkey still had to catch up with advanced nations in terms of economic development and industrialization. With the start of the planned development period in 1963, the demands related to industrialization and urbanization in Turkey increased energy consumption almost three times in 1970 [1]. Turkey is highly dependent on imports to meet its energy needs. Due to the lack of fossil resources, the dependence level in Turkey is around 70%, indicating this could rise to over 80% by 2030. Turkey meets

*Correspondence: hozbay@bandirma.edu.tr

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40% of its energy needs with oil currently and 90% of the oil supply is imported from the Russian Federation and the Middle East (Iran, Saudi Arabia, Syria, and Iraq). Compared with the European Union, Turkey is more dependent on imports, and instability in the Middle East affects Turkey much more. Therefore, Turkey should diversify its energy resources. While natural gas met 18% of the energy need in 2000, it is observed that it increased to 28.36% in 2020.[1] This makes Turkey pretty much foreign-dependent because Turkey currently imports almost all of its gas supply [2]. Therefore, Turkey aims to increase its renewable resources and share of domestic lignite and to reduce its import dependency and share of natural gas [3]. Objectives of the Turkish government in the electricity sector are listed as follows:

- Diversifying primary energy resources,
- Increasing efficiency in electricity production and consumption,
- Reducing the cost of electricity and end-user prices,
- Using domestic energy resources, including increasing the share of renewable energy resources,
- Developing regional connections and participating in regional markets,
- Creating a good investment environment for the new production capacity as well as the transmission and distribution networks,
- Creating an eco-friendly energy system and investing in environmental improvement projects for existing power plants in this sense.

With its young and growing population, low electricity consumption per capita, rapid urbanization, and strong economic growth, Turkey has been one of the fastest-growing energy markets in the world for nearly twenty years [4]. The electricity demand in Turkey is rapidly growing. It increased from 56.8 TWh in 1990 to 128.5 TWh in 2000 and to 210 TWh in 2010. In 2019, it reached 304.2 TWh, and electricity generation reached 304.8 TWh.[2] According to this scenario, electricity consumption is expected to reach 375.8 TWh in 2023 with an average annual increase of 4.8%. As of the end of September 2019, the installed capacity of our country has reached 91.340 MW. The increase in electricity generation in recent years has remained below the growth in demand for electricity. Therefore, Turkey has become an obvious importer of electricity since 1997.[3]

Medium- and long-term forecasting of energy demand needs to be made in order to be a country with a strong industry and thus high living standards. Overestimation of energy demand creates excess in resources, and underestimation can cause serial energy crises. The State Planning Organization (DPT) has initiated the usage of simple regression techniques for energy forecasting. Similar studies are being conducted by the Ministry of Energy and Natural Resources of Turkey. Starting in 1984, various modeling techniques have been used to forecast energy demand. Most of these techniques forecast the energy demand accurately and precautions can be taken in advance for problems that may occur [5].

[1]Elektrikport (2020). Turkey's electricity consumption in January [Online]. Website https://www.elektrikport.com/haber-roportaj/turkiye-ocak-ayi-elektrik-istatistikleri-2020/22507ad-image-0 [accessed 08 April 2020].

[2]Energy (2020). Turkey's Electricity Consumption [online]. Website https://www.enerjiatlasi.com/elektrik-tuketimi/ [accessed 08 April 2020].

[3]Electricity (2018). Republic of Turkey Ministry of Energy and Natural Resources. [Online]. Website https://www.enerji.gov.tr/tr-TR/Sayfalar/Elektrik Electricity [accessed 10 April 2020].

In the literature, many definitions and comparisons of forecasting methods have been presented by various researchers. Time series analyses such as ARIMA, statistical models, and other numerical methods such as genetic algorithms, particle swarm optimization, artificial neural network, and support vector machines are used for forecasting electricity demand [6]. Regression techniques, which are very easy to use, are widely applied in forecasting electricity demand. "Nonparametric regression" technique is used with the Vilar and other semifunctional partial linear model to estimate electricity demand and price of the following day. The models were applied to observed data and compared with the naïve and ARIMA models [7]. Taylor used statistical forecasting methods for short-term electricity demand forecasting. In order to adapt to the seasonal cycle throughout the year, he applied three double seasonal forecasting methods to 6 years of French and British data [8]. Fan and Hyndman proposed "semiparametric models" to forecast the relationship between demands and inputs such as calendar variables, delayed actual demand observations, and historical and average temperature. Their methods were applied to the National Electricity Market of Australia to forecast half-hourly electricity demand for up to a week [9]. Taking holidays and weekends into account, Hyndman and Fan then calculated the intensity forecasting and exact probability distributions of the future values of possible demand [10]. A similar regression approach was obtained by McSharry et al. to analyze the relationship between demand and other variables [11]. Wang and Ramsay developed a forecasting based on "neural network" for spot pricing of electricity, which focuses especially on weekends and public holidays [12]. Srinivasan et al., on the other hand, developed a similar approach for forecasting electricity demand, focusing on weekends and public holidays [13].

Long short-term memory (LSTM), which is a type of a recurrent neural network, shows a good performance in several fields such as language modelling and speech recognition [14]. LSTM is also successfully used in projection of energy consumption. In a study that was carried out to estimate household energy consumption [15], it was determined that the proposed LSTM model provided efficient and consistent estimations by showing the highest performance based on the existing competitive criteria. Similarly, in a short-term load estimation for individual households, it was reported that the LSTM approach showed a better performance than other algorithms in its functions [16]. In an application of the LSTM approach in electricity load estimation in smart grids by using a recurrent neural network, it was stated that the short-term electricity load time series was difficult due to its nonlinear, nonstationary and nonseasonal status. According to the experiment results, LSTM showed a good performance despite all these difficulties [17].

As understood from the studies in the literature, the factors that affect electricity consumption may be listed as the economy, industry, seasons, temperature of the environment, solar radiation, humidity, wind speed, workdays, and gross domestic product. In addition to these, it is understood that special days or irregular holidays also have a strong effect on energy demand [18, 19]. Energy companies regulate their production and transmission plans, taking the effects of the holiday into account.[4] The effects of irregular holidays was taken into consideration by Braubacher and Wilson in their models for hourly electricity demand. They performed an analysis by changing the holiday data with the interpolation of holiday demands before and after [20]. However, these techniques are not developed for extraordinary situations. COVID-19 or Coronavirus pandemic broke out in Wuhan, which is the capital of China's Hubei province, in December 2019 and spread all over the world like a wildfire. It has become a global public health crisis in a few months. The first case was identified in Turkey as of March 11, 2020. Then, extensive measures were taken across the country as in the rest of the world. In this study, changes in electricity production and consumption of Turkey during the coronavirus pandemic are

[4]Ontario Energy Board (2020). Electricty Price [online], Website http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices/Time-of-Use+Holiday+Schedule [accessed 29 April 2020].

analyzed in accordance with the decisions taken in the country.

The rest of the article was organized as follows: Section 2 gives the outlook of energy in Turkey. Section 3 demonstrates the effects of COVID-19 on energy consumption. Section 4 presents forecasting energy consumption during COVID-19. Section 5 discusses results. Section 6 draws the conclusions.

2. The outlook of energy in Turkey

The need for energy resources is increasing day by day in order to meet the energy demand arising as a result of advancing technology and increasing population. Due to the decrease in fossil fuel reserves and increasing environmental concerns, the supply of electrical energy appears to be an important problem today. Imported energy resources used in primary energy supply in 2015 in Turkey is 75.9%. This situation not only causes the country to be foreign-dependent on energy but also creates an environmental disadvantage. Turkey recorded a current account deficit of 33.1 billion dollars in 2016, and with an increase of 42.3% in 2017, it is recorded as 47.1 billion dollars. The most important components of this current account deficit are energy imports, which consists of imports of oil and its derivatives [21].

Turkey's economy has shown an average growth rate of 5% in recent years. This situation was reflected in the energy demand [22]. The amounts of electricity production from domestic resources and total electricity production in 2000–2018 in Turkey are given in Table 1.

Table 1. Electricity production of Turkey in years

Year	Produced by domestic resources (GW)	Total production (GW)	Year	Produced by domestic resources (GW)	Total production (GW)
2000	68750.8	124921.6	2010	96352.3	211207.7
2001	61469.0	122724.7	2011	101626.1	229395.1
2002	64712.2	129399.5	2012	104148.4	239496.8
2003	61878.9	140580.5	2013	103845.0	240154.0
2004	71266.1	150698.3	2014	94155.5	251962.8
2005	72747.7	161956.2	2015	120354.7	261783.3
2006	80125.2	176299.8	2016	135536.5	274407.7
2007	78159.9	191558.1	2017	134469.6	297277.5
2008	79647.5	198418.0	2018	149001.4	304801.9
2009	81101.4	194812.9			

When the electricity production between 2000 and 2018 is analyzed, it is seen that there is a continuous increase except for the crisis years (2001 and 2009). Although the utilization rate of domestic resources in energy production varies by years, according to Table 1, the highest value was achieved in 2000 with 55% and the lowest in 2014 with 37.4%. The distribution of energy produced between 2015 and 2019 on a resource basis is given in Figure 1.[5]

The installed capacity of Turkey between 2000 and 2019 is given in Table 2.[6]

[5]TEIAŞ (2020). Turkey Electricity Generation, Transmission Statistics [online], Website https://www.teias.gov.tr/trTR/turkiye-elektrik-uretim-iletim-istatistikleri [accessed 08 April 2020].

[6]EIGM (2020). General Directorate of Energy Works Reports [online]. Website www.enerji.gov.tr [accessed 10 April 2020].

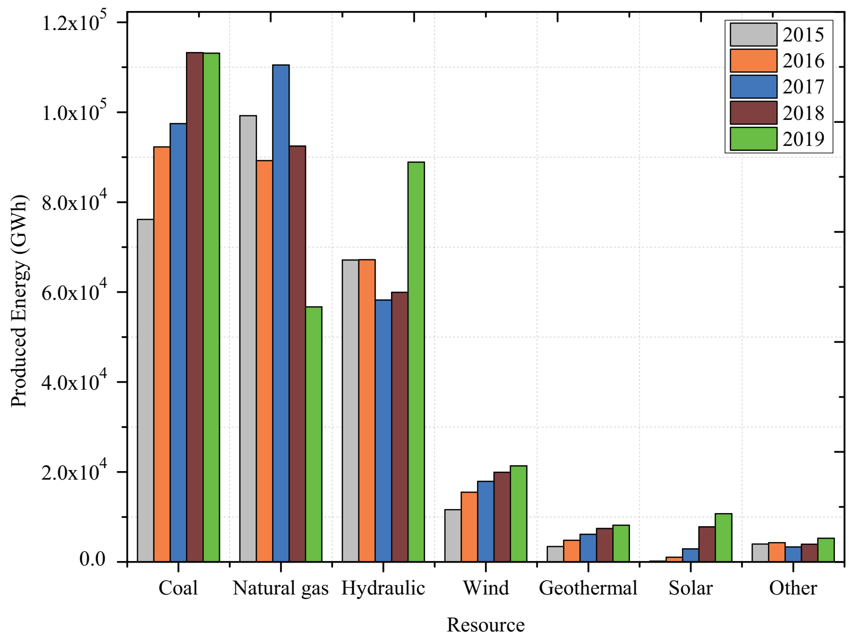

Figure 1. The distribution of energy produced in 2015–2019 on a resource basis.

Table 2. Installed capacity of Turkey by year.

Year	Installed power (MW)	Year	Installed power (MW)
2000	27264.1	2010	49524.1
2001	28332.4	2011	52911.1
2002	31845.8	2012	57059.4
2003	35587.0	2013	64007.5
2004	36824.0	2014	69519.8
2005	38843.5	2015	73146.7
2006	40564.8	2016	78497.4
2007	40835.7	2017	85200.0
2008	41817.2	2018	88550.8
2009	44761.2	2019	91267.0

When Table 2 is examined, it is observable that Turkey improves its installed capacity continuously. As of the end of February 2020, the installed capacity of Turkey reached 91406 MW. The distribution of installed capacity by resources as of the end of September 2019 is given in Figure 2. Additionally, as of the end of September, the total number of power plants, including unlicensed ones, is 8096. Fifty-two of these resources are based on geothermal, 68 on coal, 262 on wind, 330 on natural gas, 669 on hydroelectric, 6435 on solar, and 253 on other resources.

The amount of the total installed capacity of energy investments was 2821 MW in Turkey in 2019. The distribution of these investments by resource is given in Figure 3.

Turkey is an important energy corridor between Europe and Asia. It is vital for Turkey to provide safety of the industrial supply of energy to sustain its economic growth. With this purpose, the government announced

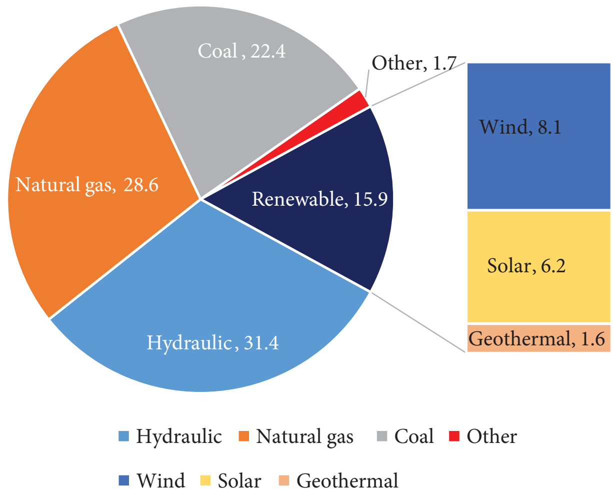

Figure 2. The distribution of installed capacity by resource (%).

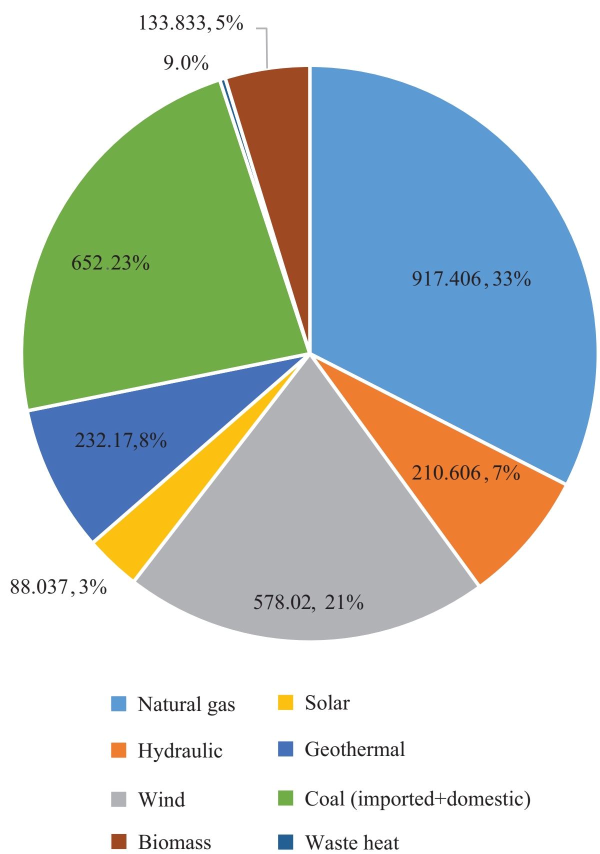

Figure 3. Energy investments by resource.

the Vision 2023 objectives in 2013 and enacted the law numbered 6446 [22]. Opening the way for renewable energy investments with this law, it is aimed to encourage domestic energy resources in the field of energy and increase the share of renewable energy to 30% by 2023[7]. Licensed power plant investments by fuel type in the last two years are given in Figure 4[8].

Considering the investments made, including the hydropower investments, it is seen that the number of investments in renewable energy is approximately 7.5 times higher than the number of investments in fossil fuels. Therefore, both the protection of the environment and the safety of energy supply will be provided with the investments made in Turkey. Moreover, contributions can be made to the reduction of the current account deficit.

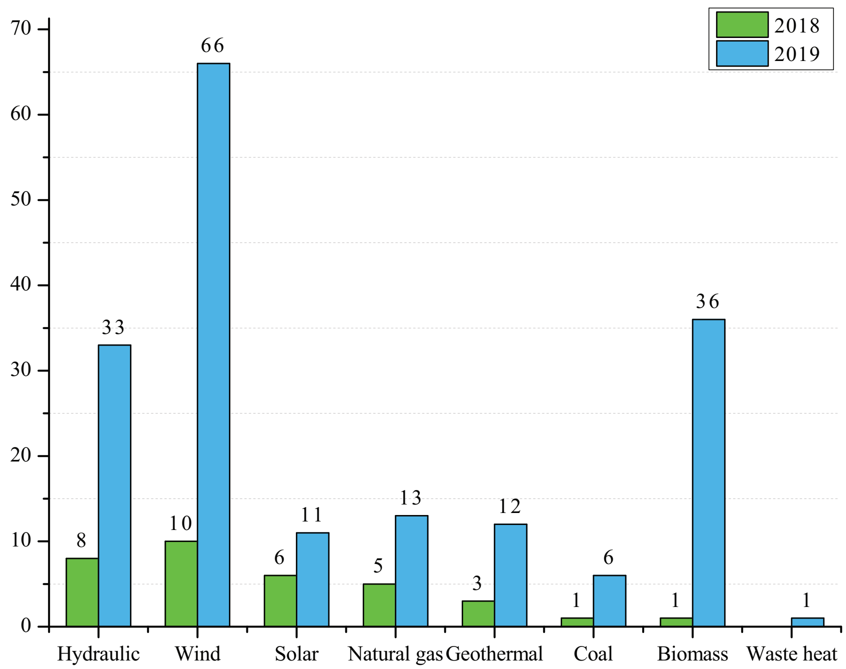

Figure 4. Licensed power plant investments by fuel type in the last two years.

3. Effects of COVID-19 on energy consumption

The major disruption caused by the COVID-19 crisis once again showed how much electricity modern societies need. Millions of people have now begun working on the internet to do their jobs at home and started using e-commerce sites for shopping, and video platforms for entertainment [23]. It is known that reliable electricity resource forms the basis of all these services. Additionally, it is one of our basic needs for devices such as refrigerators, washing machines, and bulbs, which are indispensable for vital activities at home today, to function smoothly. Moreover, in many countries, electricity is critical for the operation of ventilators and other medical devices for patients in hospitals. In such uncomfortable and rapidly developing situations, electricity ensures punctual transmission of important information between governments and citizens, and between doctors and patients [24]. As a result of the measures taken against the coronavirus, factories and enterprises stopped their activities in many countries, and electricity demand decreased by approximately 15% as of March. Some of these

[7]Official Gazette (2020). Electricity Market Law [online]. Website https://www.resmigazete.gov.tr/eskiler/2013/03/20130330-14.html [accessed 11 April 2020].

[8]EPIAŞ (2020). Licensed Power Plant Investments [online], Website https://seffaik.epias.com.tr/transparency/uretim/lisansli-santral-yatirimlari.xhtml [aceessed 11 April 2020].

economies, such as Spain and California, are among the those with the highest share in the wind and solar power generation in the world. If electricity demand drops rapidly while the weather conditions remain the same, the share of variable renewable energies such as wind and solar may be higher than normal. Electricity distribution companies must constantly balance supply and demand. If the wind and solar energy meet a significant part of the demand, the systems must maintain flexibility in order to rapidly increase other production resources during a change of supply, such as when the solar or wind energy become unavailable [25].

Renewable energy sources such as wind and solar power have experienced tremendous growth over the past two decades, created entirely new global industries, and helped to prevent a significant level of greenhouse gas emissions. It is evident that the utilization of renewable energy resources is crucial in order to meet world climate targets and other long-term sustainable energy targets. However, the crisis caused by COVID-19 appears to distort the momentum significantly. Falling costs and support of strong policy were made renewable energies increasingly attractive and competitive. However, it is possible to face difficulties due to pressure on capital and private budgets, such as supply chain interruptions that may lead to delays in the completion of projects caused by the coronavirus crisis and the possible decrease in investments, along with the uncertainty of future electricity demand. At this point, economic incentive packages that aim to put the global economy back on track will be important. The governments need to encourage technological innovations by reducing the structural benefits that renewable energy resources can help in terms of economic development and employment, as well as in reducing emissions. A few months before the coronavirus pandemic appeared in October 2019, the International Energy Agency (IEA) predicted that 2020 would be a record year for renewable electricity operations[9] [10]. Factories in China produce approximately 70% of the global solar panels supply. Of this, 1% to 10% comes from Chinese companies operating in Southeast Asia. In February, solar panel production facilities in China had to halt production due to coronavirus-related precautions in several major cities. When the wind power supply chain is compared to the solar panel, it is much more interconnected globally. Europe is an important production center for wind turbines. Europe experienced disruptions in the supply of parts from China in February. Production facilities, especially in Italy and Spain, were closed in mid-March due to tight precautions. Additionally, it seems that increasing precautions of the pandemic in other countries will delay the completion of many projects worldwide. System operators continue to develop ways to manage these challenges. However, extraordinary developments such as social distance and curfew that all countries take during global pandemics require new methods to be developed. The sudden slowdown in the industrial and commercial activities in Turkey and a large part of Europe significantly reduced electricity demand. The measures taken within the scope of the Covid-19 outbreak, the fact that stopping or decreasing the production of automotive and subindustry facilities regarded as large-scale industrial organizations, iron and steel facilities, and some other organizations affected the electricity and natural gas consumption curves downward[11].

In Turkey, it was determined in a report prepared by Google for 16 February–29 March period that community mobility in shopping and entertainment areas decreased by 75%, in parks by 58%, and in workplaces by 45%. Moreover, it has been determined that mass transportation has decreased by 71% and there is an increase of 17% in residence areas[12]. The first Covid-19 case in Turkey was seen on 11 March. Then, by taking

[9]IEA (2019). World Energy Outlook [online]. Website https://www.iea.org/reports/world-energy-outlook-2019 [accessed 12 April 2020].

[10]GWEC (2020). Wind Industry COVID-19 Response Hub [online], Website https://gwec.net/wind-industry-covid-19-response-hub/ [accessed 12 April 2020].

[11]IEA (2020). Commentary [online]. Website https://www.iea.org/commentaries/the-coronavirus-crisis-reminds-us that-electricity-is-more-indispensable-than-ever [accessed 12 April 2020].

[12]Google (2020). COVID-19 Community Mobility Report [online]. Website https://www.gstatic.com/covid19/mobility/2020-03-

various precautions, the pandemic period was attempted to be taken under control. Milestones are given in Table 3[13,14,15] during the pandemic period. The events are expressed in numbers and shown in Figure 5. Thus, the effect of the precautions taken on energy consumption can be examined explicitly.

Table 3. Milestones of Covid-19 and the restrictions in Turkey

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No	Events
1	The first case was announced in Turkey. (11 March 2020)
2	Activities such as national and international meetings, congresses, conferences were postponed. (13 March 2020)
3	Within the scope of the Covid-19 precautions, passenger transportation in 9 European countries and 16 countries is prohibited. (14 Mart 2020)
4	Formal education was interrupted in primary, secondary, high schools, and higher education institutions. Some operations of businesses (theater, cinema, etc.) stopped (16 March 2020)
5	The first death due to coronavirus occurred in Turkey. (17 March 2020)
6	Curfew restrictions were imposed on citizens aged 65 and over. (21 March 2020)
7	In 30 metropolitan and 1 province, entry and exit of the vehicles were closed with some exceptions. Curfew imposed for those who are under 20 years old in the whole country.(3 April 2020)
8	The government declared curfew in 31 provinces (11-12 April 2020)
9	The government declared curfew in 31 provinces (18- 19 April 2020).
10	The government declared curfew in 31 provinces (23-26 April 2020)

Restrictions imposed on 31 provinces are the leading provinces of Turkey in terms of economy, production, and business. As of December 31, 2019, population of Turkey is 83 million 154 thousand 997. The total population of the 31 provinces that declared curfew is 65 million 265 thousand 543. This figure is 78.486% of the total population[16]. Turkey's total exports in 2019 are 180 billion 848 million 602 thousand dollars. The total export figure of the 31 provinces was 173 billion 49 million 454 thousand dollars. When the number of initiatives based on annual business registration in 2018 is analyzed, Turkey's total number of initiatives is 3 million 845 thousand 951 and the total number of initiatives in the specified provinces appears to be 3 million 144 thousand 384. Thus, it is clear that those provinces are in the leading positions in Turkey[17]. Considering the consumption amounts invoiced in 2018, the total consumption amount of the 31 provinces, which were restricted, was 189.9 TWh. This figure constitutes 81.28% of all of the consumption[18].

In Figure 6, actual consumption data for the first 4 months of 2019 and 2020 are given comparatively. Total consumption in the first two months of 2019 was 25368.8 GW and 22630.4 GW, respectively. In 2020, total consumption in January was 26173.6 GW and total consumption in February was 24213.5 GW. Accordingly,

29 [accessed 06 April 2020].

[13]Anadolu Agency (2020). Infographics [online]. Website https://www.aa.com.tr/tr/info/infografik[accessed 19 April 2020].

[14]Circular Letter (2020). Quarantine over 65 years of age [online]. Website https://www.icisleri.gov.tr/65-yas-ve-ustuile-kronik-rahatsizligi-olanlara-sokaga-cikma-yasagi-ek-genelgesi [accessed 14 April 2020].

[15]Listelist (2020). Canceled and Postponed Activities Due to Corona Virus [online], Website https://listelist.com/corona-iptal-edilen-etkinlikler/ [accessed 14 April 2020].

[16]TUIK (2020). Address Based Population Registration System Results [online], Website http://tuik.gov.tr/PreHaberBultenleri.do?id=33705 [accessed 12 April 2020].

[17]TUIK (2020). Statistics Reports [online], Website https://biruni.tuik.gov.tr/ilgosterge/?locale=tr [accessed 13 April 2020].

[18]EPDK (2018). 2018 Electricity Market Development Report [online] Website https://www.epdk.gov.tr/Detay/ DownloadDocument?id=X/fUh6+7kaM= [accessed 16 April 2020].

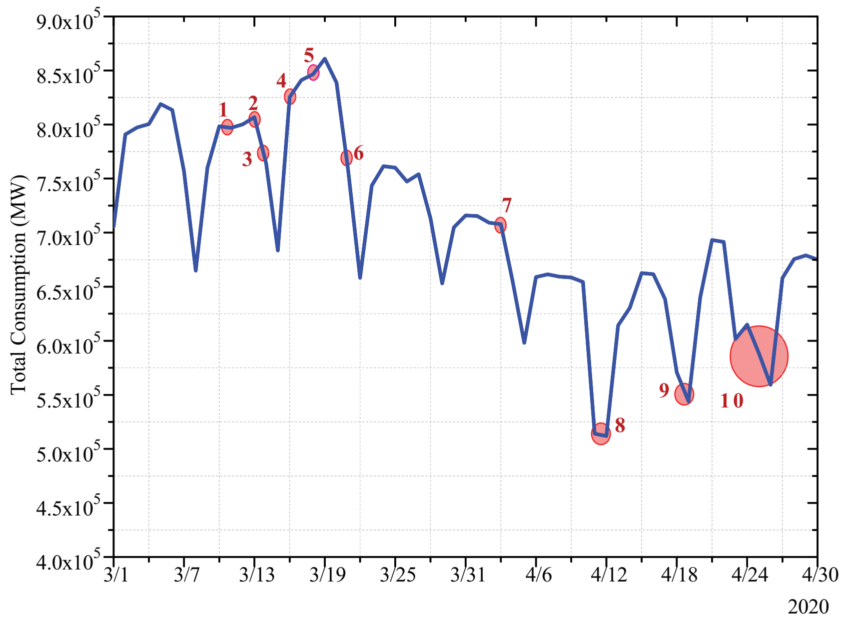

Figure 5. Events after the first COVID-19 case was confirmed in Turkey and energy consumption.

an increase of 3.17% and 6.99% in consumption was observed for the first two months in 2020, respectively. Following the start of the pandemic period and especially the restrictions, the energy consumption trends decreased in March and April compared to the general consumption trend. While the total consumption in March 2019 was 23793.9 GW, it was 23740.1 GW in 2020. The biggest impact was experienced in April. While the consumption of April 2019 was 22611.1 GW, the consumption of April 2020 was 19103.8 GW with a decrease of 15.5%[19]. When the decreases in energy consumption in April were analyzed, serious decreases were observed especially during restrictions.

4. Forecasting of energy consumption during COVID-19

High living standards, rapid development of technology, and increased population increase the consumption of electricity to a serious extent. In this case, to provide energy supply, it is a requirement to make the correct planning. By using various projection methods and determining the short-, medium-, and long-term usage amounts, it may be possible to take the necessary precautions. In the literature, forecasting energy consumption methods are divided into two main categories. One of them is statistical methods and the other is computational intelligence (CI). Since energy consumption data are not linear, CI methods like artificial neural network (ANN), fuzzy logic, and expert systems are proven to be more effective [26]. Many studies have analyzed and compared different ANN methods and their performance for energy consumption forecasting [27]. In this study, the external multivariable input model NARX-ANN and long short-term memory network have been used due to both superiority of performance and simplicity of structure.

[19]Elektrikport (2020). Electricity statistics in March [online]. Website https://www.elektrikport.com/haberroportaj/turkiye-mart-ayi-elektrik-istatistikleri-2020/22605ad-image-0 [accessed 16 April 2020].

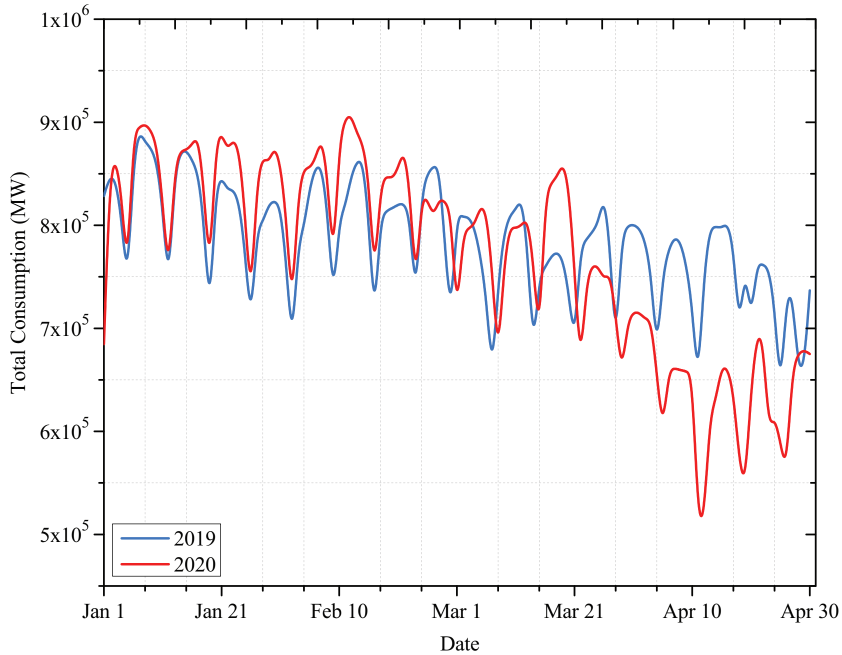

Figure 6. The actual consumption for the first 4 months of 2019 and 2020.

4.1. Long shor-term memory (LSTM) ANN

Recurrent neural networks (RNNs) are neural networks using recurrence that basically uses information from a previous feed forward pass over the neural network as seen in Figure 7. When the recent research articles are examined, RNNs are extremely successful when applied to problems where input data is in the form of a series of predictions [28].

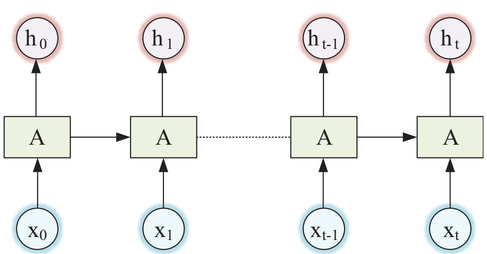

Figure 7. Architecture of recurrent neural network.

Input sequence is given as $[x_1, x_2, ..., x_{\mathrm{k}}]$ and let $x_{\mathrm{i}} \in \mathbb{R}^d$. Here the value of k may vary, as different samples may have different sequence lengths. In each stage of the RNN model, a hidden state is created in the array $[h_1, h_2, ..., h_{\mathrm{k}}]$. Depending on the previous hidden state $h_{\mathrm{t\text{-}1}}$ and the current input x_{t}, the activation of the hidden state at time t can be written as follows:

$$h_{\mathrm{t}} = f(Wx_{\mathrm{t}}, Uh_{\mathrm{t\text{-}1}}) \tag{1}$$

The weight input and hidden state are compressed together by a logistic sigmoid function or hyperbolic tangent $(tanh)$ to ensure that the gradients are applicable for back-propagation [29].

Introduced in 1997 by Hochreiter and Schmidhuber, the LSTM is a special type of RNN used in deep learning. The existence of a correlation between the data stored at different times is called ”long-term dependence”. It is aimed to store and transmit the state information of the artificial neural network when processing sequences in RNNs [30]. LSTMs help maintain error that can propagate through time and layers. LSTMs contain information in gated cells that decide what to hide and when to open and close, and when to read, write, and delete. These cells learn when to allow, drop, and delete data through iterative estimates, back-propagation errors, and adjustment of weights. Figure 8 shows data flow and control through memory cells and ports.

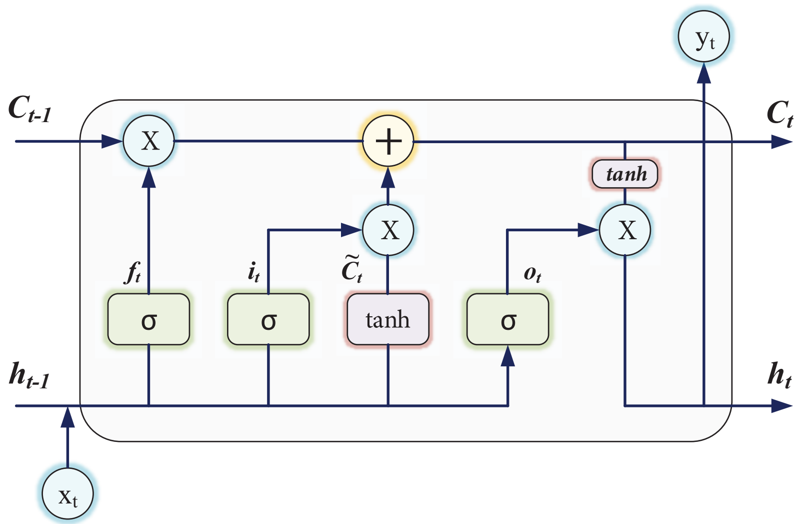

Figure 8. Long short-term memory network block diagram.

Inside the LSTM module, there are three separate gates with their labels, forget, input, and output. The forgetting gate decides how much information should be forgotten and how much will be passed on to the next step. It uses a sigmoid (σ) function that generates a value between 0 and 1 for this process. 0 means that no information should be transmitted, and 1 means that all information should be passed [31]. It is possible to express the mathematical model of this process as follows:

$$f_{\mathrm{t}} = \sigma(W_{\mathrm{f}} \cdot [h_{\mathrm{t\text{-}1}}, x_{\mathrm{t}}] + b_{\mathrm{f}}) \tag{2}$$

In the next step, it is decided what information should be stored. As a first step at this stage, a $2^n d$ sigmoid (σ) function decides what values should be updated. Subsequently, through a ($tanh$) function, it creates a vector of new candidate values, expressed as C_t, and then these two processes are combined. It is possible to express this process as follows:

$$i_{\mathrm{t}} = \sigma(W_{\mathrm{i}} \cdot [h_{\mathrm{t\text{-}1}}, x_{\mathrm{t}}] + b_{\mathrm{i}}) \tag{3}$$

$$C = tanh(W_{\mathrm{c}} \cdot [h_{\mathrm{t\text{-}1}}, x_{\mathrm{t}}] + b_{\mathrm{c}}) \tag{4}$$

After the candidate values have been determined, the new state information of the memory cell must be calculated. The new state information calculation process and the output of the system h_{t} are expressed as follows:

$$C_t = f_t * C_{t\text{-}1} + i_t * C_t \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t\text{-}1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t * tanh(C_t) \tag{7}$$

4.2. Nonlinear autoregressive exogenous (NARX) ANN

The NARX is a recurrent dynamic neural network. It has feedback connections which enclose several layers of the network. In order to obtain the full performances of the NARX neural network for nonlinear time series prediction, its memory ability is utilized using the past values of predicted or true time series. The input-output relationship of ANN dynamics used in NARX is defined as in Equation 8 [32]:

$$y(t) = F[x(t), x(t - \triangle t), ..., x(t - n\triangle t), y(t), y(t - \triangle t), ..., y(t - m\triangle t)] \tag{8}$$

where m is the number of time delays at the back-propagation, n represents the number of time delay steps at the input, and F represents a nonlinear function. In addition to the x external variable, the lagged y variable is also included in Equation 8. Time, Covid-19 precautions, and weather variables are external inputs and $y(t)$ is internal input. The ANN is trained using the real values of y_i and is used in a closed-loop, feeding back each monthly step estimate of y_i to produce the forecasting of the next day. The structure of MATLAB NARX-ANN is shown in Figure 9 [33].

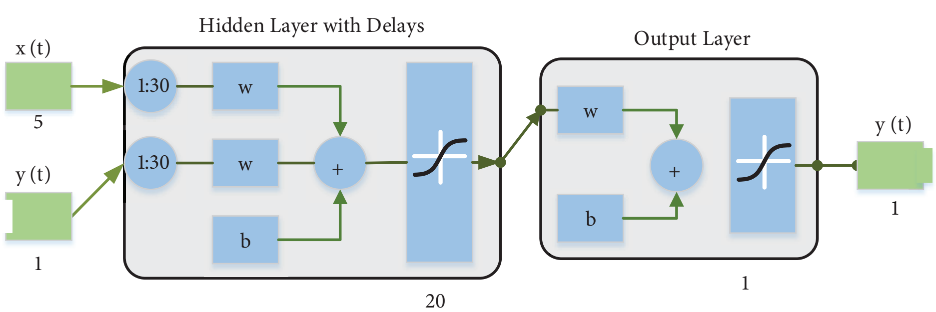

Figure 9. The structure of MATLAB NARX-ANN.

The network was trained with the Levenberg–Marquardt back-propagation algorithm using last year's 365-day data. The NARX operation starts with a many-layered feedforward neural network structure to learn the behavior during the $y(t)$ output using the $x(t)$ inputs, and the regression model for the y output layer is as in Equation 9:

$$y_t = \Phi[\beta_0 + \sum_{i=0}^{q} \beta_i h_{ij}] \tag{9}$$

β_0 is the output deviation, β_i is the output layer weights, i is the subarray of q neurons, Φ is $\Phi(x) = x$, and the activation function represents the output with the linear function. The hidden layer given in Equation

10 is used to flatten or limit neuron weights:

$$h_{\mathrm{it}} = \Psi[\gamma_{\mathrm{i0}} + \sum_{j=1}^{n} \gamma_{\mathrm{ij}} x_{\mathrm{jt}}] \tag{10}$$

Ψ represents the activation function for hidden neurons, γ_{i0} is the input deviation, γ_{ij} is the weights of the input layer, and j is the subarray of the n inputs. Equation 11 is obtained by combining Equations 9 and 10:

$$y_{\mathrm{t}} = \Phi\beta_0 + \sum_{i=0}^{q} \beta_{\mathrm{i}} \Psi 0[\gamma_{\mathrm{i0}} + \sum_{j=1}^{n} \gamma_{\mathrm{ij}} x_{\mathrm{jt}}] \tag{11}$$

Autoregression, which is a dynamic term, is added to the hidden layer in here. Moreover, Equation 12 is obtained by adding ℓ index to N layers, k index to the multidimensional structure of τ outputs, and extending Equation 11:

$$y_{\mathrm{t}}^{k} = \Phi\beta_0^{k} \sum_{\ell=1}^{N} \sum_{=1}^{q} \beta_{\mathrm{i}}^{\ell} \Psi[\gamma_{\mathrm{i0}}^{\ell} + \sum_{j=1}^{n} \gamma_{\mathrm{ij}}^{\ell} x_{\mathrm{jt}} + \sum_{r=1}^{q} \delta_{\mathrm{ir}} h_{\mathrm{r,t\text{-}1}}] \tag{12}$$

δ_{ir} represents the delayed weight and $_{r}, t-1$ refers to the back-propagation term. The equation obtained is used to express the NARX neural network used in this study. This equation is also used for open-loop and closed-loop systems. y values are obtained from known past values of output in open-loop network. Therefore, a regular login to the network is made. The values of y are obtained from the predicted value of the output [34].

4.3. Proposed approach

In order to produce a model that can provide sufficient prediction accuracy with the minimum input set, a statistical analysis of the correlation between input and output by the estimated value is required for each variable. Figure 10 shows the preparation and process method of forecasting data via ANN to achieve the best performance with the smallest input set. External and internal (time-delayed) inputs are shown in Table 4.

Table 4. Inputs of ANN model

External inputs	Internal input	Time delay
Day	Consumption	Last 1 Month
Week		
Month		
Temperature		
Pandemic precautions		

Evaluation metrics are approaches used to measure the quality of the intelligent models. As there are many different types of evaluation metrics available to test a model, in this paper, root mean square error

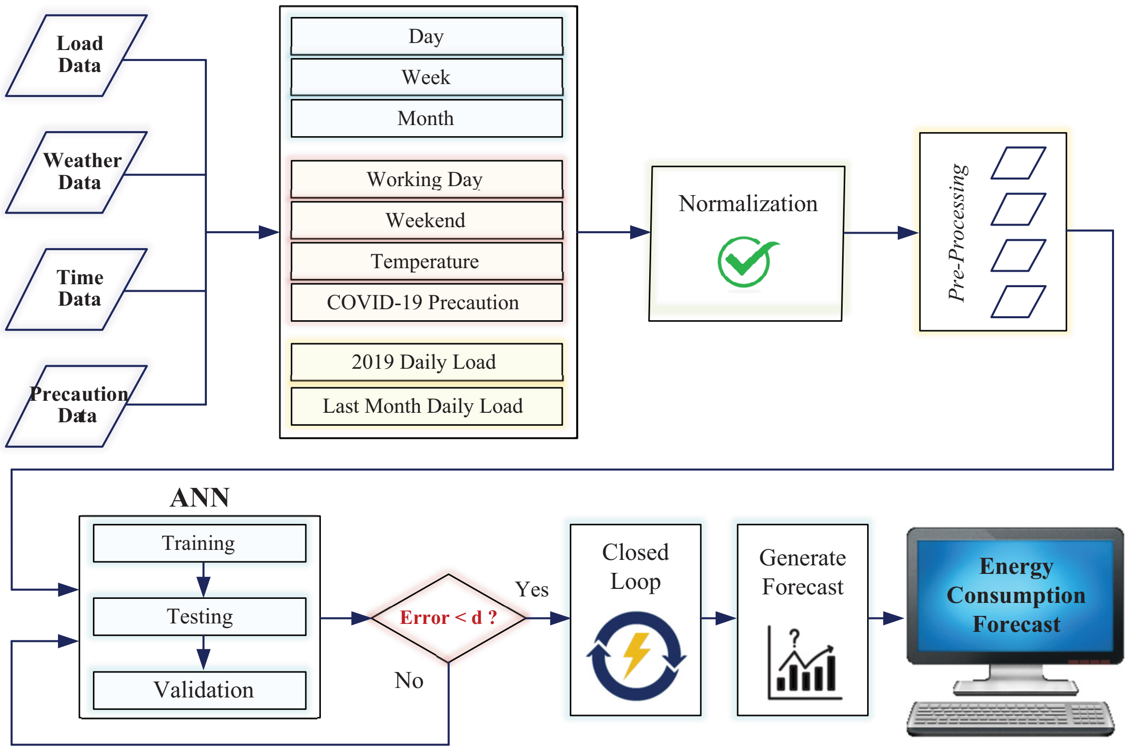

Figure 10. Proposed ANN method flow diagram.

(RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) metrics were used to evaluate forecasting performance. Mathematical approaches for these metrics can be given as follows [35]:

$$\text{RMSE} = \frac{\sqrt{\sum_{t=1}^{T}(y_{\mathrm{i}} - y_{\mathrm{i}})^2}}{\sqrt{T}} \tag{13}$$

$$\text{MAE} = \frac{\sum_{t=1}^{T} \mid y_{\mathrm{i}} - y_{\mathrm{i}} \mid}{T} \tag{14}$$

$$\text{MAPE} = \frac{100\%}{T} \sum_{t=1}^{T} \mid \frac{y_{\mathrm{i}} - y_{\mathrm{i}}}{y_{\mathrm{i}} \mid} \tag{15}$$

where y_{i} refers to the actual load demand, y_{i} refers to the corresponding forecasting load demand, and T is the total number of forecasting points. After the forecasting data is produced in a closed loop, an error occurs between the actual consumption data and the closed-loop forecasting output because we use historical data for verification. This error is the error value expressed in the literature as a forecasting error.

5. Results and discussion

In this study, one-year energy consumption data such as year, month, day, work-day, weekend, air temperature, and curfews during the pandemic period were divided into groups and some of them were used for testing. Then, these data were prepared to match the input neurons. The resulting data set is divided into training, verification, and test data sets. The training set is trained with the Levenberg–Marquardt training algorithm to achieve open loop weights for NARX. A test and verification data set was made and repeated 10 times for 5–20 neurons in 5-neuronal increments. In the end, the closed-loop network is created by choosing the most suitable open-loop network according to the minimum MAPE criterion to produce a daily energy consumption forecasting data with date, weather, and pandemic precaution data. Thus, the designed model uses its output consumption forecasting as an input to generate the next day's energy consumption forecasting. Eventually, daily consumption forecasting is obtained as a result of these transactions.

Adam optimizer was used to update model parameters during the back-propagation phase for LSTM. Adam is an optimization technique that has been widely used in recent deep learning studies. The Adam algorithm converges faster to optimum degree compared to traditional gradient descent algorithms, and accordingly, the use of time and computational resources is reduced. Default parameters were used in the training phase, such as learning rate = 0.001, $\beta_1 = 0.92$, $\beta_2 = 0.995$, and $\varepsilon = 10^{-8}$.

The designed NARX and LSTM models were simulated using MATLAB 2018 (Licence No: 40692431) and data were obtained. The NARX and LSTM were trained in the open-loop using 2019 actual consumption data and then produced in the closed-loop. With ANN, the consumption prediction of the first day is calculated with the trained network and sent to the input as back-propagation to obtain the second value. Figure 11 shows the open-loop data of the NARX and LSTM ANN models.

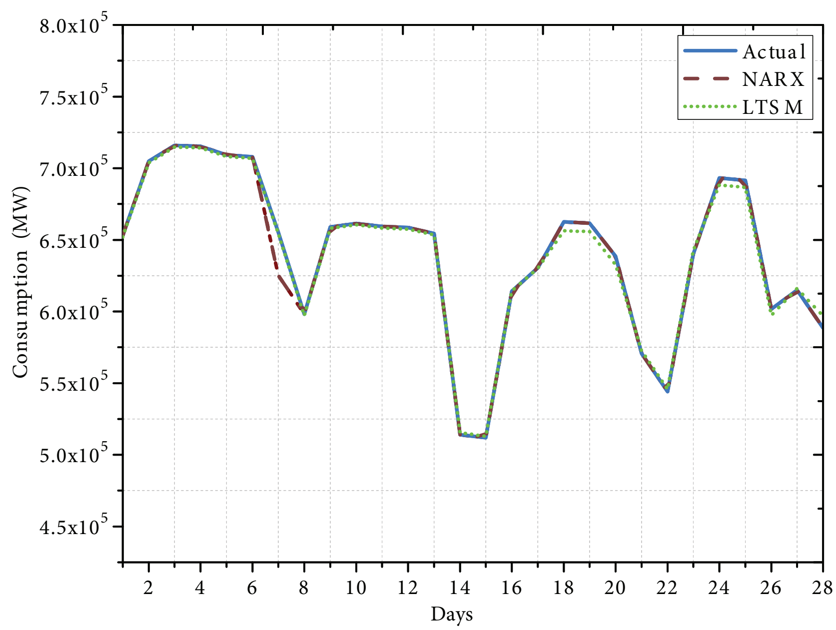

Figure 11. Four-week predictions and actual consumption data with NARX and LSTM.

The training process was started at different random weights, and the results of forecasting were recorded. Since the neural network-based approaches are highly intuitive, different initial values can lead to different results. RMSE, MAE, and MAPE values obtained with different initial weights are given in Table 5. Figure 12 shows the forecasting data produced by NARX and LSTM ANN until the end of June and the actual data until May. The standard error of the regression between forecasting data and actual data is expressed as a measure of performance [36].

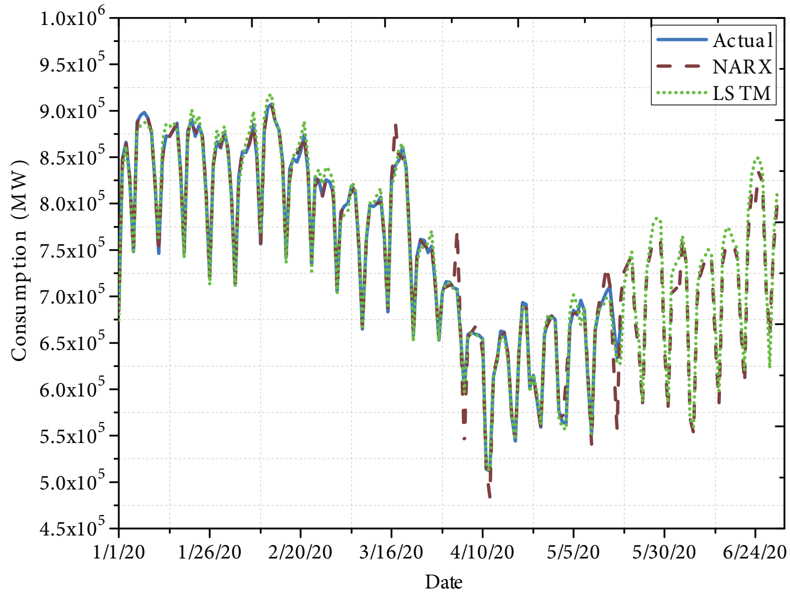

Figure 12. Six-month forecasting data and four-month real consumption data with NARX and LSTM.

Table 5. RMSE, MAE, and MAPE values obtained with different initial weights.

		Test 1	Test 2	Test 3	Test 4	Test 5	Mean
NARX	RMSE	10030.96	9108.256	9034.396	10821.96	9237.208	9646.556
	MAE	9277.563	7696.161	7233.547	10410.87	7857.275	8495.083
	MAPE	1.3453	1.0540	0.9539	1.5716	1.0739	1.1997
LSTM	RMSE	8347.938	8231.400	8164.651	9065.275	9780.125	8717.878
	MAE	7403.743	7251.929	6816.018	8742.050	9809.942	8004.736
	MAPE	0.991266	0.9728	0.8805	1.2417	1.4506	1.1074

When Turkey's electricity production is analyzed, except in 2001 and the crisis year of 2009, it is confirmed to be on a steady increase. The impact of the country's growth rate (5%) is very important in this. However, besides this increase, serious fluctuations in energy consumption may occur due to pandemics such as COVID-19, which greatly affects humanity. Therefore, the effects of such special cases can be reduced by analyzing current situations, taking precautions, or developing procedures. Today, it is important to manage these critical processes successfully for both the consumer and the grid, especially, considering energy safety for developing countries. Governments should not ignore local and natural energy resources in their economy package prepared for global pandemics like COVID-19.

Energy independence is important for developing countries such as Turkey. This can largely determine the ability of countries to be self-sufficient. In this respect, renewable energy resources are of great importance for countries like Turkey. Energy demand decreases with the suspension of the factory and enterprise services. At this point, meeting these demands with renewable energy resources seems to be an advantage for countries to produce their own energy. However, balancing demand and supply with wind and solar power that are unstable may be a major disadvantage in maintaining the stability of the network.

6. Conclusion

Considering the pandemics are a fact of the globalizing world, it is inarguable that countries should be ready for the next periods in terms of energy supply. In the current situation, although many organizations and industry stopped their operations, the energy sector continues its activities for all humanity. Thus, both the activities of health institutions and human activities such as distance education, and work continue. The pandemic situations like COVID-19 reveal the necessity of countries to have energy infrastructures ready and to have sufficient manpower working in the energy sector. It is essential to make a planning to ensure electrical energy supply. By using various estimation methods, short-, medium-, and long-term usage amounts can be determined and necessary precautions can be taken. In the study, NARX and LSTM have been applied to forecast energy consumption. Thanks to the proposed estimation methods, the actual energy consumption of January–April 2020 has been successfully estimated. In addition, the energy consumption estimate including the effect of COVID-19 was made between January and June 2020. It is considered that the comments and forecasts presented in this study would be helpful for energy planners to build future scenarios about the Turkish electricity consumption.

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