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Research Article

Forecasting of monthly electricity generation from the conventional and renewable resources following the corona virus pandemic in Türkiye

Erol Kurt
Gazi University, Technology Faculty, Department of Electrical and Electronics Engineering, TR06500 Beşevler Ankara, Türkiye, ekurt@gazi.edu.tr

Reşat Kasap
Gazi University, Faculty of Science, Department of Statistics, TR06500 Beşevler, Ankara Türkiye, rkasap@gazi.edu.tr

Kayhan Çelik
Gazi University, Technology Faculty, Department of Electrical and Electronics Engineering, TR06500 Beşevler Ankara, Türkiye, kayhancelik@gazi.edu.tr, kayhancelik1923@gmail.com

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Abstract: In the present paper, a forecasting study on the monthly electricity generation of Türkiye from the conventional and renewable resources is performed. The effect of the CoVid-19 pandemic on the sector has been considered. For this aim, the trend before the pandemic has been initially considered and later the post-pandemic situation has been handled. It has been observed that the electricity generation supply/demand mechanism changes drastically compared to the pre- and post-pandemic cases. The rate of the generation from the renewable resources especially shows a sharp variation compared to the rates from the fossil fuels. According to the forecasting scenario, in 2021, the electricity generation shows different attitudes with regard to the resources used. In 2022, especially increasing trends are expected for wind, biogas, natural gas, imported coal and fuel oil, whereas diesel and mineral coal are expected to be decreased in Türkiye.

***Keywords**:* *Covid19 pandemic, Energy generation, Exponential smoothing, Forecasting, Time Series Modeling (SARIMA),*

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1. INTRODUCTION

In these days, it is a quite important for the governments and companies to forecast the electricity generation and consumption with the high reliability, accuracy and precision. Because there are many advantages and benefits of accurately estimating electricity generation and consumption such as planning the necessary production schedules according to the needs, making maintenance and repair plans according to the time [1] [2]. The another important issue of forecasting of the production/ consumption scheme with the high rate of accuracy gives opportunity for making the electricity supply-demand relationship more reliable for the energy policy studies of the countries and communities [3].

Due to the unique structure of the electricity market from a producer to a consumer and due to its non-storable character, it is necessary to make sure that there is electricity demand in an environment where electricity generation is intended, while on the other hand, it is necessary to present the electricity needs for potential and existing customers uninterruptedly, reliably with an affordable cost in a competing market. Therefore, it is essential to implement practical and easy forecasting study of the electricity generation and consumption.

The electricity constitutes the majority of the energy we use in our daily lives. In today's world, the load estimation has an important role in the planning, operation and control of power systems. If the electricity load prediction is more than electricity demand, it causes too many power supply units to step in, triggering excessive energy intake and providing unnecessary reserves. Even as occurred in the past, disasters may occur instantly within the entire country or a part of it in the case of unbalanced load conditions. Conversely, low load estimation may cause the system to operate in a risky region, resulting in insufficient supply reserve. At the same time, load estimates form the basis of many decisions made in energy markets world-widely. The electric energy prices, which are optimized according to the load forecast results leads to the following positive output in the policies:

- *It enables electricity markets to be planned and operated in an efficient, transparent, reliable way that meets the needs of the sector,*
- *It presents a basis portfolio for the competing companies,*
- *The optimum prices can be obtained.*

On the other hand, it is clearly seen that the energy generation and consumption behavior of the countries indicate substantial changes during the Corona Virus pandemic time. The restrictions over the consumers who have household and industry related consume have played an important role in that non-standard behavior. In this context, many developed countries such as USA, China, Britain, Germany, Spain, Italy and developing ones such as Türkiye, Russia, Brazil have been affected negatively from the pandemic. Recently, many studies have been performed on the effects of the pandemic on social life, the environment, animals and plants [4] [5] [6] [7]. For instance, the impact of the Covid-19 pandemic restrictions on the electricity consumption of some European countries is examined by Bahmanyar et al. [8]. The impact of the Covid-19 pandemic restrictions to the daily global CO_2 emissions is also reported by Le Quéré et al [9], Gillingham et al [10] and Wang et al [11]. Besides, the relationship between air pollution and COVID-19-related deaths in some French cities are examined by Magazzino et al [12]. In addition to the Covid-19 effects on social life and environment, it also effects the electricity generation and consume of the users from all over the world. Since the restrictions change from one country to other, of course the effect of pandemic to the electricity generation and consume differs from one country to other. Thus, the story of each country can shed a light to the characteristic production and consume scenarios of individual countries in crisis such as pandemic, war, etc. To use of this data can assist to form smart systems in near future, too.

In addition, apart from the pandemic effects, the world population is estimated to be 10 billion in 2040 or at least in 2050. Such a population growth shows that electricity consumption will increase significantly for the future world. By focusing on the next a few decades, two-thirds of the world population will live in locations, which are far from rural areas. For instance, every four months there exists a population increase as much as China's largest city world-widely. The most important artifact on electricity generation in order to meet the growing energy demand is the increasing of the harmful emissions such as CO_2, NO_X. It is a reality that the worldwide emission amount in the past years exceeded 45% of the values twenty years ago in average. Thereby, the generation of electricity from environment-friendly renewable resources gets more importance to reduce this artifact.

Studies on electricity generation /consumption have recently increased especially in developed countries in parallel with the smart energy network applications. Indeed, present world has many tools to screen and control the generation / consumption of electricity over the internet with reliable electronic devices such as PLC, SCADA and internet of things (IoT) based applications [13] [14]. It is clear that there is a need for innovative studies on the efficient consume of electricity for all energy consuming devices. In the present world, energy efficiency is considered as a new energy resource itself [15]. Therefore, the energy generation /consumption data becomes important for the current and future projection of the issue to avoid the losses occurring due to unbalances between supply and demand.

The first forecasting studies in Türkiye were performed by the Ministry of Energy and Natural Resources (MENR) during the 1970s [16]. Other important development on the subject was the estimation and planning for the energy need which was made by the MENR and the State Planning Organization (SPO) in 1984 [16]. The historical development of the energy market in Türkiye can be briefly summarized as follows: In 2001, energy market regulatory authority (EMRA) was founded. In 2004, the temporary balancing and settlement regulation was published. In 2009, the day-ahead planning mechanism was launched and hourly pricing and settlement was initiated. In 2015, Turkish Energy Exchange Company (EPIAS) founded. It provided all hourly energy production and consumption information data on its web page and intraday market was opened.

The following examples can be given to the previous load estimation studies on Türkiye. The neutral networks based on the recursive multilayer perceptron (MLP) were used estimating the amount of daily electricity consumption by Topalli and Erkmen [17]. In another study of the same authors, a hybrid learning scheme combining the off-line learning with real-time forecasting was developed [18]. Artificial neural networks (ANNs) were used in another study for the estimation of long-term electricity consumption and the obtained results were compared with the results made with Box-Jenkins models and regression technique, as a result, it was proven that ANNs were efficient estimation tool for the electrical energy consumption [19]. In another paper, an ANN model was considered for the short term peak, total load forecasting of the day and medium term monthly load forecasting in power distribution systems [20]. The ANN model was used by Kavaklioğlu and his colleagues for the forecasting the electricity consumption until 2027 with the data between 1975 and 2006 by the help of the some economic parameters like population, gross national product, imports and exports [21].

In a different work, electrical energy demand forecasting was made by using the Adaptive Network Based Fuzzy Inference Systems - ANFIS and Autoregressive Moving Average-ARMA techniques. A comparison between these methods was made in demand estimation [22]. The long term electricity demand forecasting was presented by Demirel and his colleagues by using three-layered backpropagation and a recurrent neural network with the economic data for the years 2008 to 2014 and obtained results were compared with the official forecasts [22]. Kucukali and Baris presented a fuzzy logic methodology with parameter of the gross domestic product (GDP) based on purchasing power parity for estimating the short-term gross annual electricity demand [23]. Kıran et al., proposed the models for the forecasting the electricity energy demand, which were based on the *n* artificial bee colony and particle swarm optimization by using the gross domestic product, population, import and export figures of Türkiye [24]. In another work, which was performed by Tütün et al., the electricity consumption was forecasted with the LADES and RADES model [25]. The least squares support vector machines (LS-SVMs) with the independent variables of gross electricity generation, installed capacity, total subscribership and population were used for the energy consumption by Kaytez et al. [26]. The studies have shown that the fossil fuels were rapidly exhausted with the increasing energy demand and that there may be resource problems in the near future. When fossil fuels were exhausted, the ongoing discussions on the nuclear energy also emphasized the importance of renewable energy sources. Looking, all countries in the world in the field of renewable energy investments, there has been a rapid acceleration gain. Türkiye's potential in this area in developing countries qualifications considering, in order not to lose from global competition, especially wind, hydraulic and solar energy. Increasing the investments has been a complete necessity in this regard [27].

The common feature of the techniques was to use a model to accommodate past information in seasonal time series and allowing a large number of guesses at once [28]. In the present study, 365 days on a daily basis, on a monthly basis, the 12-month forecast is made at once. All statistically relevant forecast models, year-ago natural gas consumption on a daily basis, the lowest error for 2014, the highest compliance ARIMA (1,0,1) 1 (0,1,1) 365 model with 24,6% MAPE and 0,802 R2 value coefficients of this model. It is statistically significant and its remains are found as white noise same model monthly. It is observed that it has the lowest error (MAPE) and the highest fit (R2) in predictions monthly. In the estimation, the MAPE and R2 of this model are predicted as 11.32% and 0.981%, respectively. These results are showed that ARIMA models are the most suitable estimation technique among univariate techniques. One reality is that many estimations can be made at the moment and the results are acceptable for monthly and daily estimation [29].

The paper is structured as follows: Section 2, describes the methods included in the study; Section 3, includes the data and analysis that are the subject of the study; Section 4 summarizes the results with a brief conclusion.

2. MATERIAL AND METHOD

The method to be used in this study has an important place in many fields, which has a serious importance in almost every field, and to reveal the data in the form of predicting the events and situations that may occur in the future by looking at the data available up to the present time. After a prediction model is created with the time series revealed by the data taken in certain periods and the validity of this prediction model is ensured, the future prediction of the time series can be made. In this manner, as a disadvantage of the method, time series analysis may suffer from the weak data, including statistical problems with generalization from a unique work, difficulty in receiving the appropriate techniques, and issues with the accurately definition of the correct model to represent the data. Therefore, we have collected the real data from different sources and confirmed them by checking different references [1-3,16,20,25,27,28].

Method of time series analysis is major forecasting method among the statistical techniques. These methods, which are based on the use of information obtained by examining the past by various methods, in predicting the future, are used in all areas where short, medium and long term forecasts are desired. It is of great importance to predict the unknown future with the scientific methods and to make preparations for the future. The analyzing, visualizing and modelling of the data using the time series are a comprehensive study. The time series is a measurements of variables with data obtained in chronological order over time which is given in the format Z_t, $t = 1, 2, \ldots n$ with n sample sizes. Thus, t^{th} observed data over time is expressed by Z_t.

The most common univariate model degrees are briefly expressed as $(p,d,q)X(P,D,Q)$. Here, (p,d,q) shows the non-seasonal structure and (P,D,Q) shows the seasonal structure. Accordingly, the general expression of the seasonal model is given by,

$$\phi_p(B)\Phi_p(B^s)\nabla^d\nabla_s^D Z_t = \theta_q(B)\Theta_Q(B^s)A_t \quad (1)$$

Here, the seasonal polynomials of order P and Q are shown, respectively. ∇ is the non-seasonal difference operator and d^{th} order is the non-seasonal difference operator. The stationary conditions in these models are the same as in the models examined before. Accordingly, in the most general form, non-stationary and non-seasonal linear time sequences can be symbolically written as $SARIMA(p,d,q)X(P,D,Q)_s$. Finding the best model by using the *AIC* (Akaike Information Criterion). The *AIC* is formally defined as,

$$AIC(M)=n\ ln\ (\sigma_A^2) + 2M \tag{2}$$

The The Box - Jenkins methodology mainly considered as the most efficient *forecasting technique* which is Minimum mean square error forecasts for of Z_{n+1} is given below by its conditional expectation is adopted for the present work [30]:

$$\hat{Z}_n(l) = E(Z_{n+l} / Z_n, Z_{n-1}, ...) \tag{3}$$

Exponential smoothing is a technique which one updates the estimate with the help of the former information and also used in the frame of our work. The technique makes the averaging (smoothing) former values of the series decreasingly [31]. The basic exponential smoothing has a single level parameter and it can be identified as:

$$\begin{gathered} L(t)=\alpha Y(t)+(1-\alpha)\ L(t-1) \\ \hat{Y}(k)=L(t) \end{gathered} \tag{4}$$

Brown's exponential smoothing has level and trend parameters and can be described by the following equations:

$$\begin{gathered} L(t)=\alpha Y(t)+(1-\alpha)L(t-1) \\ T(t)=\alpha(L(t)-L(t-1))+(1-\alpha)T(t-1) \\ \hat{Y}_t(k)=L(t)+((k-1)+\alpha^{-1})T(t) \end{gathered} \tag{5}$$

On the one hand, Holt's exponential smoothing has level and trend parameters and can be described by the following equations:

$$\begin{gathered} L(t)=\alpha Y(t)+(1-\alpha)(L(t-1)+T(t-1)) \\ T(t)=\gamma(L(t)-L(t-1))+(1-\gamma)T(t-1) \\ \hat{Y}(k)=L(t)+kT(t) \end{gathered} \tag{6}$$

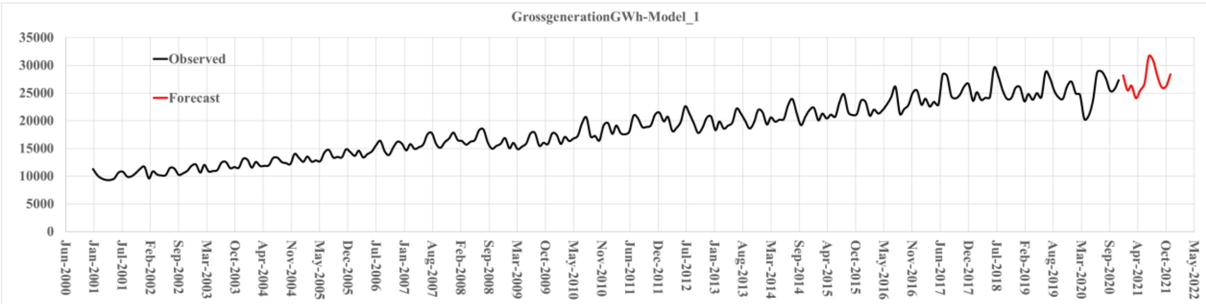
Then the best forecasting model has the smallest *Mean Absolute Percentage Error* (MAPE) as described in Ref. [31] [32]. The Mean Absolute Percentage Error is,

$$MAPE = \left(\frac{1}{F}\sum_{l=1}^{F}\left|\frac{e_l}{Z_{n+l}}\right|\right)100 \tag{7}$$

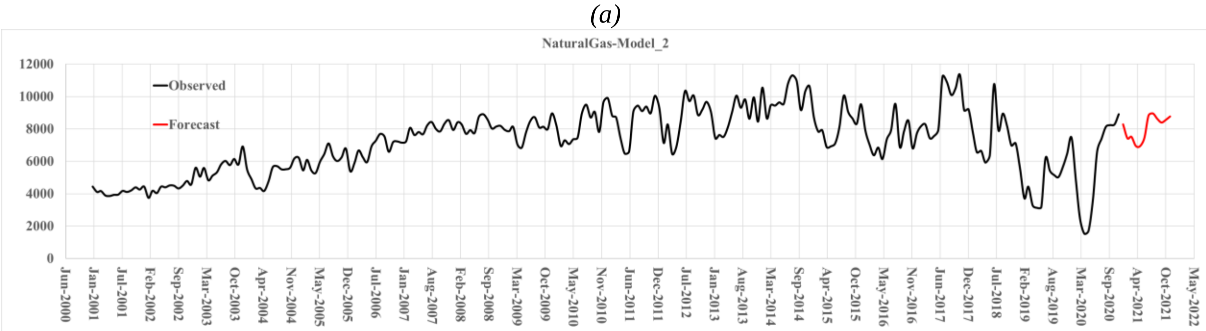
3. DATA, ANALYSIS AND DISCUSSION

In this section, we try to find out the model structure of each monthly series of electricity generation and consider the variability of the model structure from 2001 to 2020. These series are as follows: Gross generation (GWh), Natural Gas, Hydro, Biogas Waste, Geothermal, Wind, Solar, Fuel Oil, Diesel, Mineral coal, Imported coal, Asphalted, Lignite (see in Fig. 1(a-l)). To see this, the modeling processes for each series are considered by using the time series models mentioned in previous subsection. The time series models obtained for the data of 2001 and 2020 in terms of monthly series of electricity generation can be seen in Tables 1-4 in detail in the *Appendixes.*

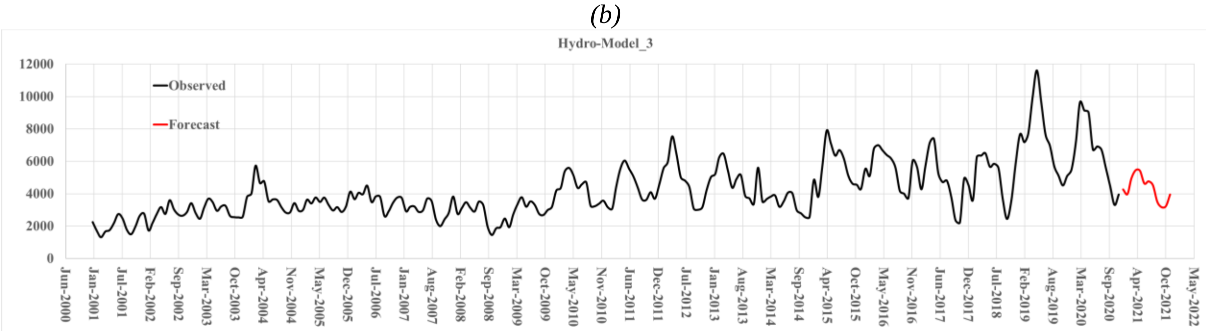
Accordingly, Natural Gas, Hydro, Diesel, Mineral Coal, Asphalted and Lignite series have Simple Seasonal model. Gross generation, Wind, Solar, Fuel Oil and Imported coal have the Winters' Multiplicative model. In addition to this, Biogas Waste has the Winters' Additive model and lastly, Geothermal has SARIMA(0,1,0)X(0,1,1) model.



(a)



(b)



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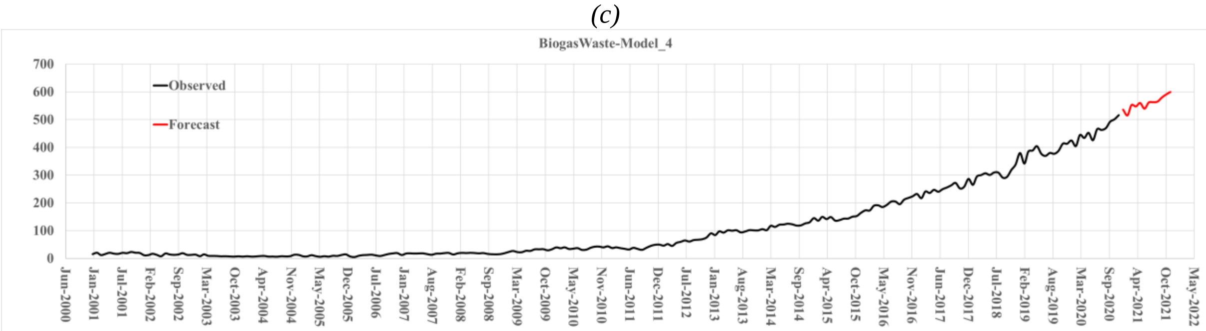

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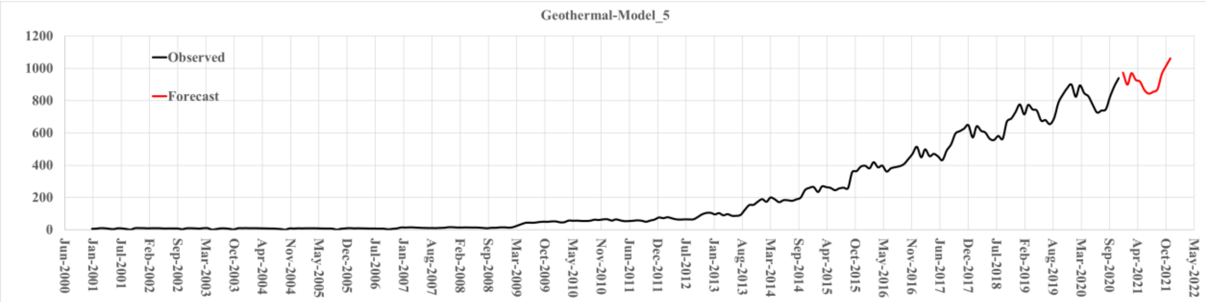
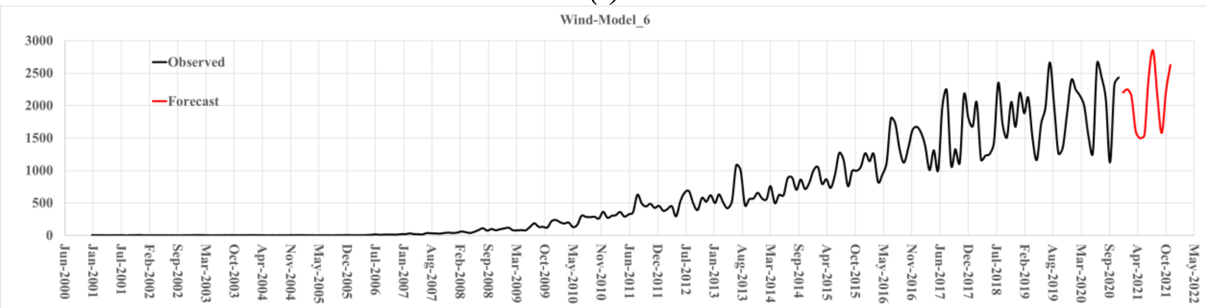
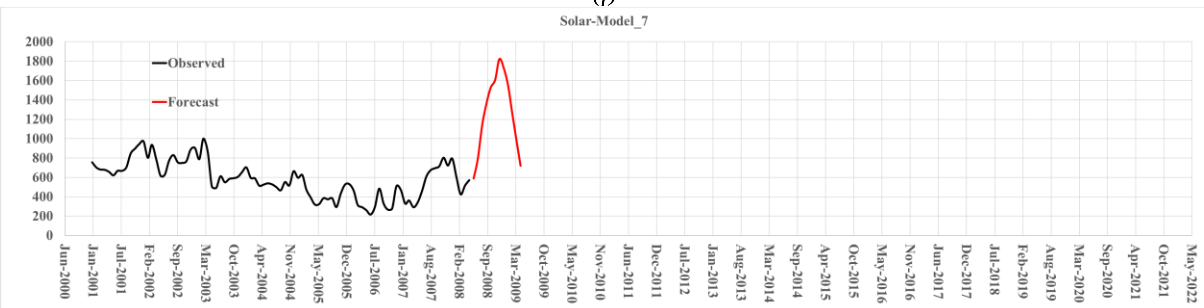

Geothermal-Model_5
Observed
Forecast

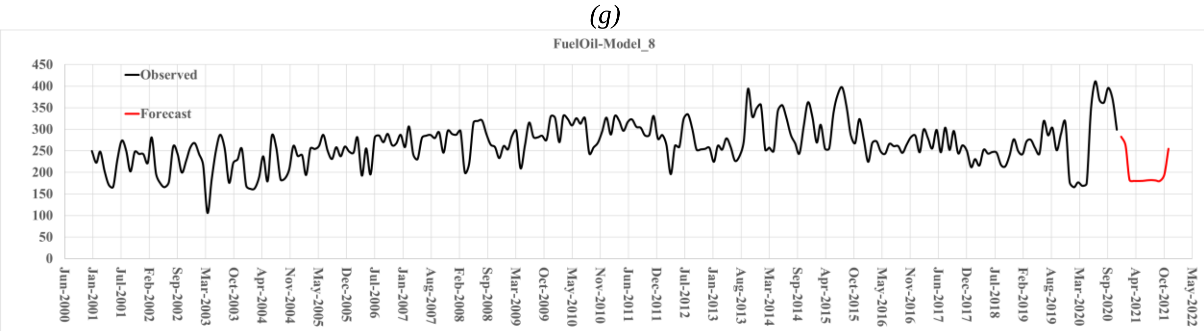
(e)


Wind-Model_6
Observed
Forecast

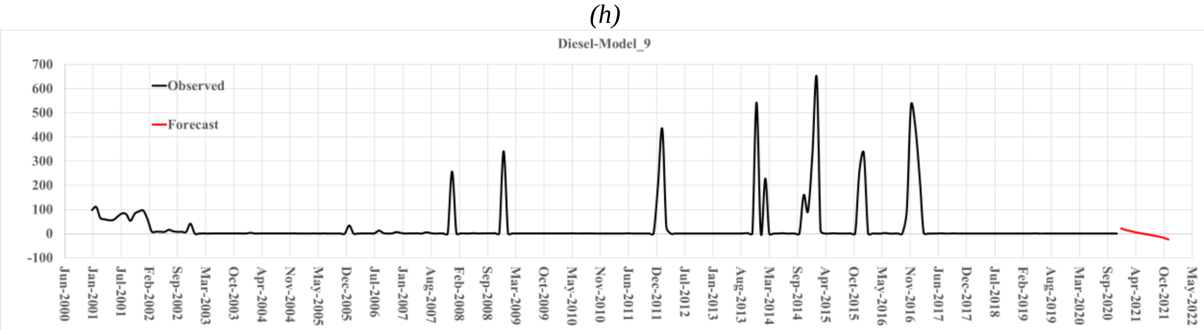
(f)


Solar-Model_7
Observed
Forecast

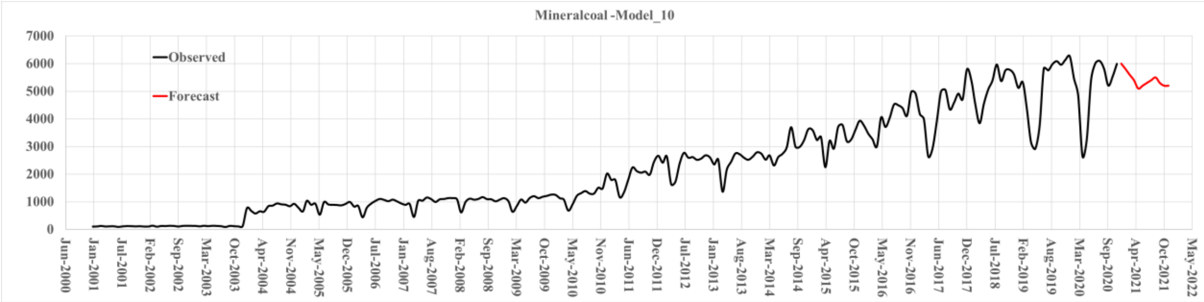
(g)


FuelOil-Model_8
Observed
Forecast

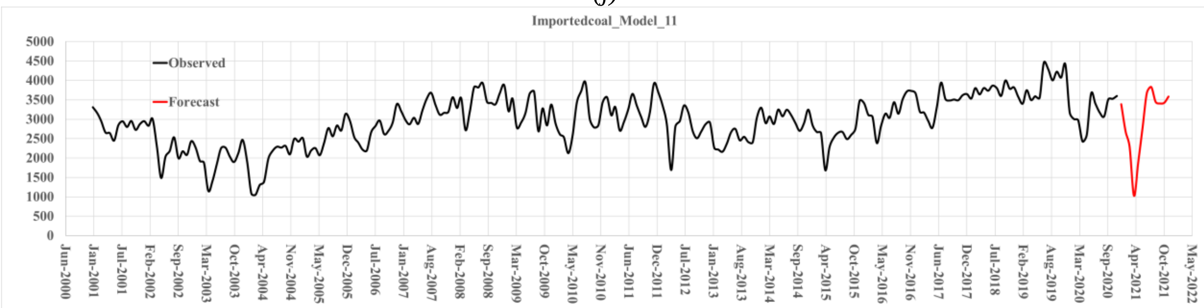
(h)


Diesel-Model_9
Observed
Forecast

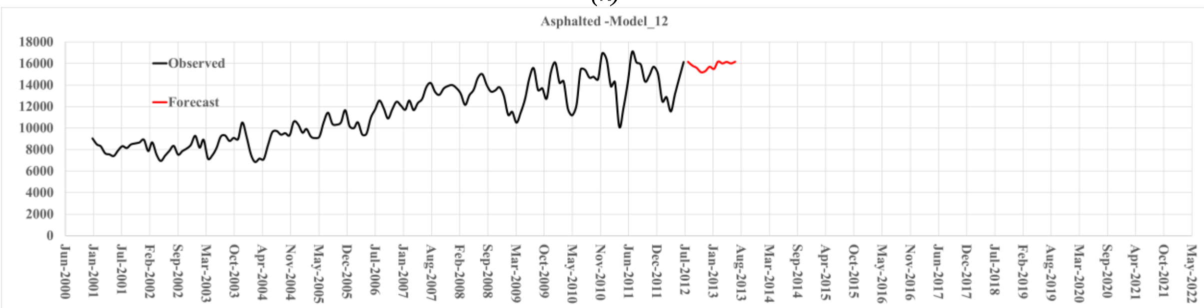
(i)



(j)



(k)

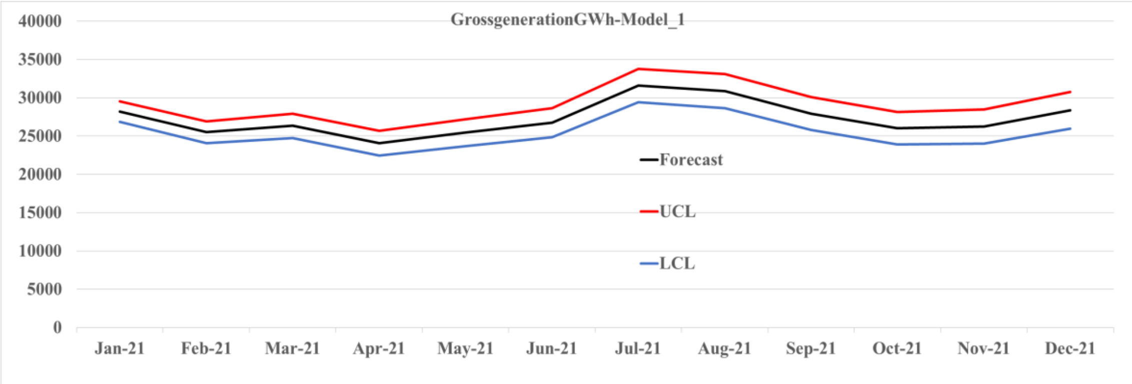


(l)

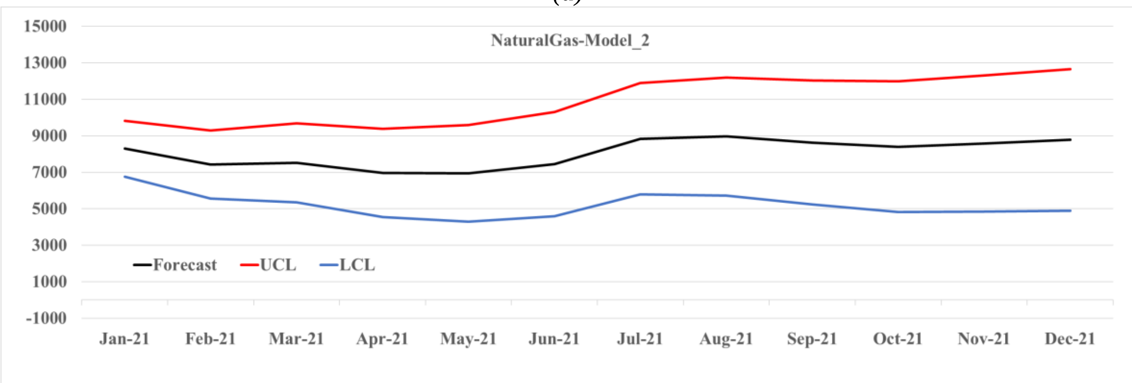
Figure 1. Plots for monthly series of electricity generation data obtained from 2001 and 2020 for various resources.

Considering Table 1-4 in *Appendixes*, all energy generation sources show seasonal characteristics. Based on Table 5 in *Appendixes*, when Figs. 1 and 2 are taken into account, this structure continues in the estimation values of 2021. With it, the Fuel oil series went down to zero; Diesel, Mineral coal, Asphalted, Lignite series follow a static process; other series are in an increasing trend. This increase can be said to be more pronounced in the Natural Gas, Biogas Waste, Geothermal, Wind, Solar and Imported coal series.

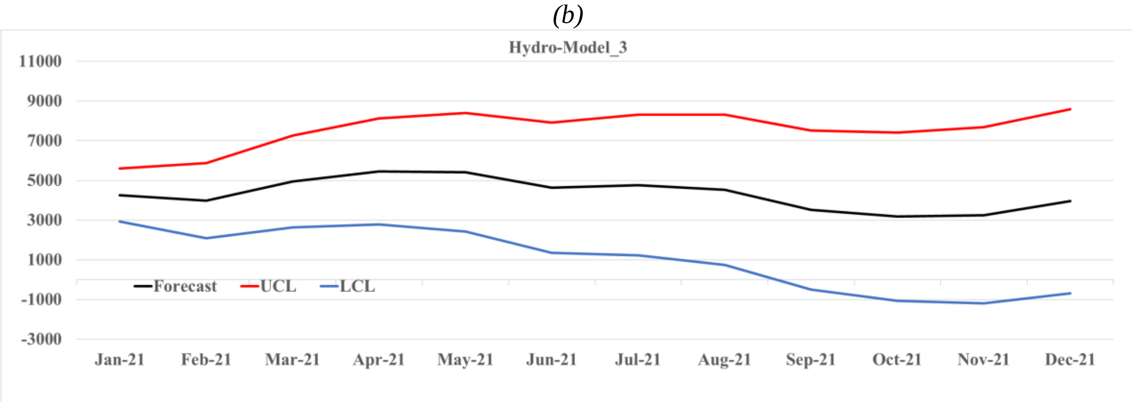
In Table 6 of *Appendixes*, the diagnostic checking of the estimated models are given. When Table 6 is carefully examined, it is seen that there are no outliers in any of the models. This is a good situation in terms of healthy modeling of the data. MAPE values are the smallest value that allows each model to be determined. R^2 values are the coefficients of determination on the coefficient side of each model and are mostly at an acceptable level. According to the Ljung-Box Q statistical values, Wind-Model_6, Solar-Model_7, Diesel-Model_9, ImportedKomur-Model_11 models are the best models obtained according to the other criteria in Table 6, but at least one of the autocorrelation of their residues according to the Ljung-Box Q statistics can be said to be different from zero. This means that until a new model is made with a larger series, further results with these models should be interpreted with caution. However, NaturalGas-Model_2, Hydro-Model_3, BiogasWaste-Model_4, TasKomur-Model_10, Linyit-Lignite-Model_13 models can be accepted as suitable models at the 0.001 significance level. The model GrossgenerationGWh-Model_1 is the appropriate model at the 0.01 significance level. Geothermal-Model_5, FuilOil-Model_8, Asphaltit-Model_12 models are suitable models with a significance level of 0.05. All the results can be seen in Figs. 2(a-m).


GrossgenerationGWh-Model_1
40000
35000
30000
25000
20000
15000
10000
5000
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

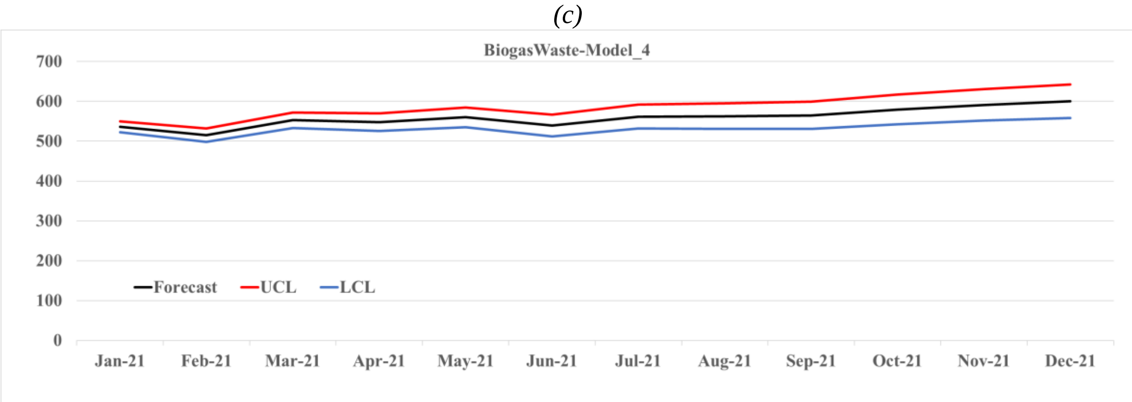
(a)


NaturalGas-Model_2
15000
13000
11000
9000
7000
5000
3000
1000
-1000
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

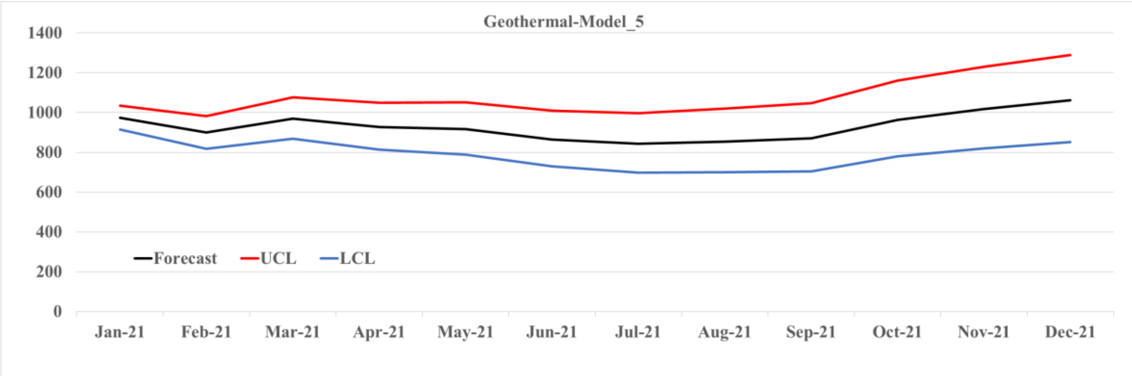
(b)


Hydro-Model_3
11000
9000
7000
5000
3000
1000
-1000
-3000
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

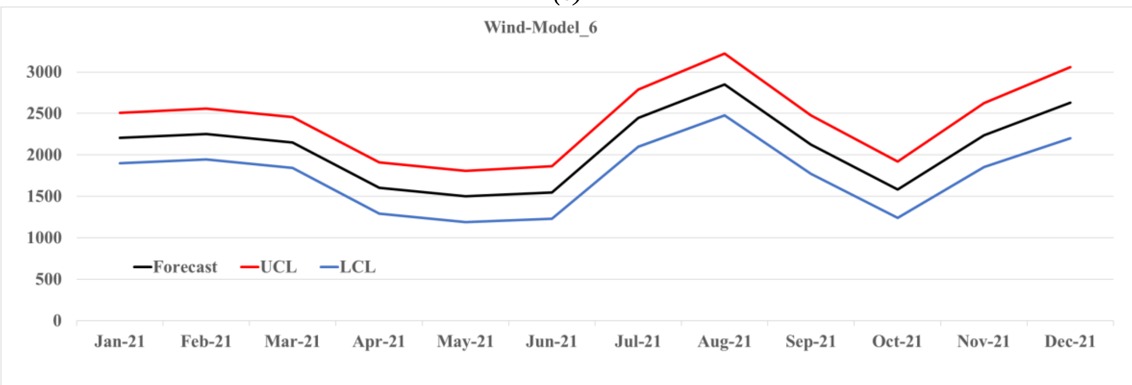
(c)


BiogasWaste-Model_4
700
600
500
400
300
200
100
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

(d)


Geothermal-Model_5
1400
1200
1000
800
600
400
200
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

(e)


Wind-Model_6
3000
2500
2000
1500
1000
500
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
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Jul-21
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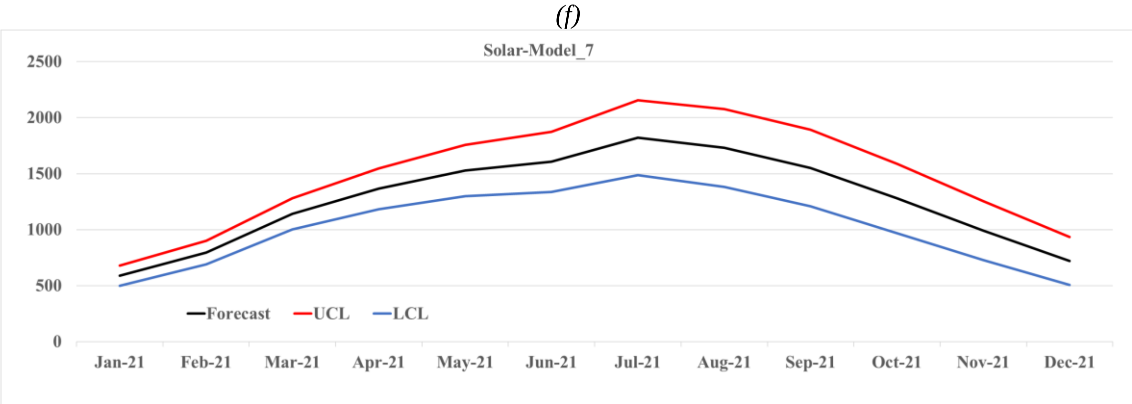
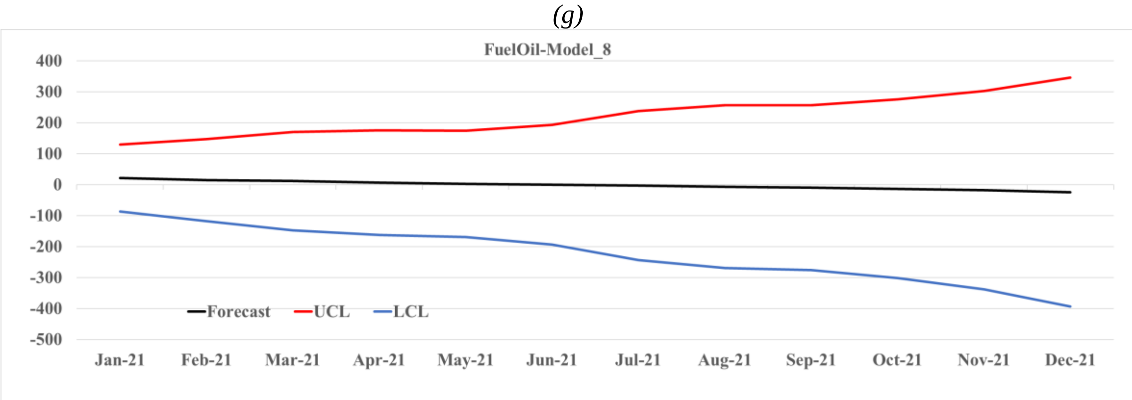
Sep-21
Oct-21
Nov-21
Dec-21

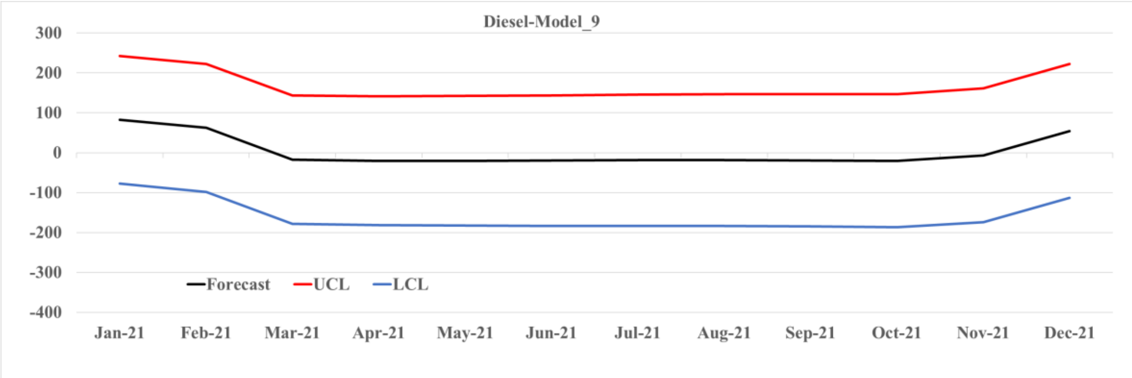
(f)


Solar-Model_7
2500
2000
1500
1000
500
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

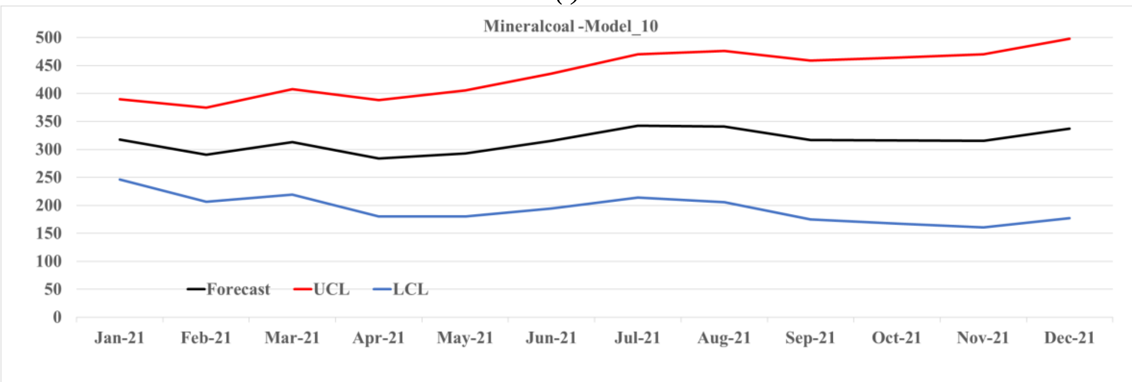
(g)


FuelOil-Model_8
400
300
200
100
0
-100
-200
-300
-400
-500
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

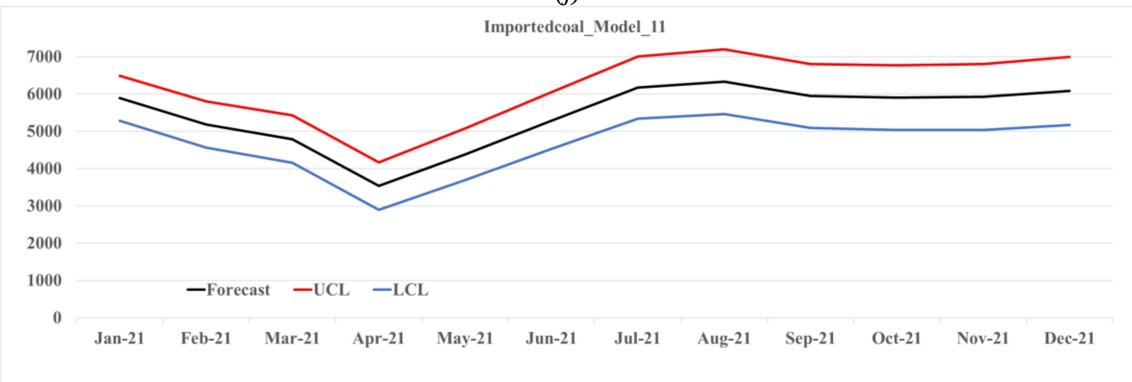
(h)


Diesel-Model_9
300
200
100
0
-100
-200
-300
-400
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

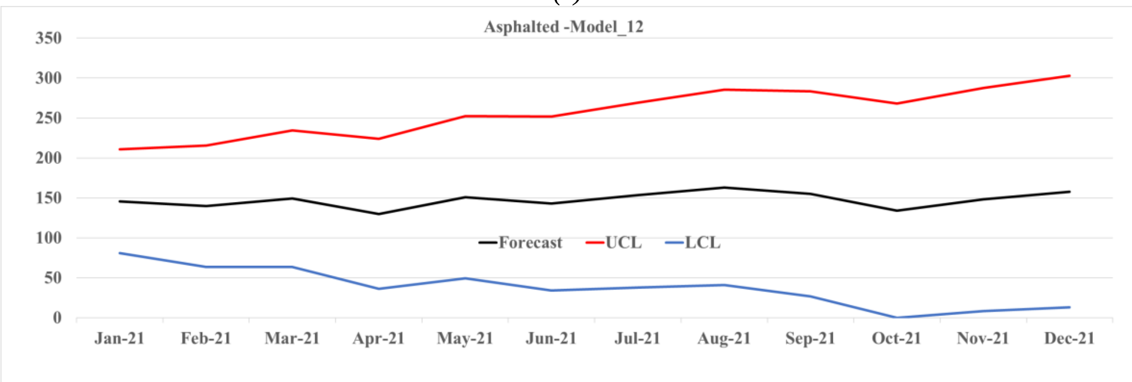
(i)


Mineralcoal -Model_10
500
450
400
350
300
250
200
150
100
50
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

(j)


Importedcoal_Model_11
7000
6000
5000
4000
3000
2000
1000
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
Jun-21
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

(k)


Asphalted -Model_12
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300
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200
150
100
50
0
Forecast
UCL
LCL
Jan-21
Feb-21
Mar-21
Apr-21
May-21
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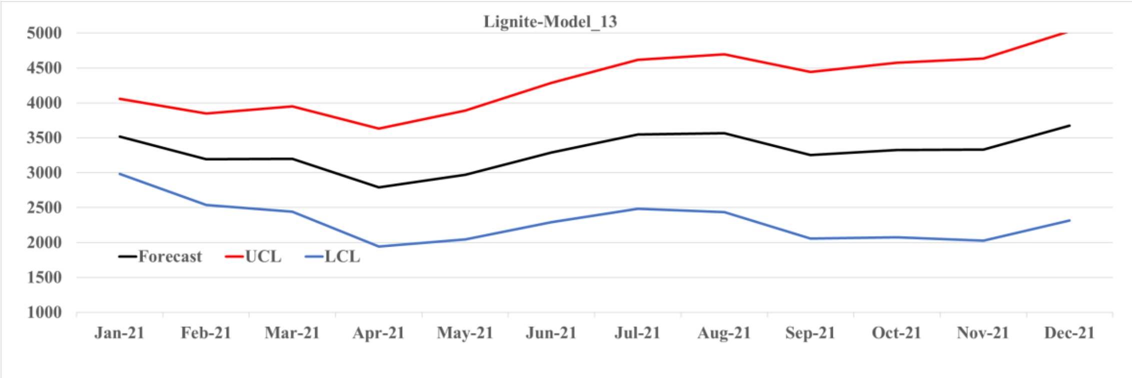
Jul-21
Aug-21
Sep-21
Oct-21
Nov-21
Dec-21

(l)



(m)

Figure 2. Plots of forecasts of 2021 for monthly series of electricity generation data obtained from 2001 and 2020 for various resources.

4. CONCLUSION

In this paper, a forecasting study on the monthly electricity generation of Türkiye during the Covid 19 pandemic is considered which are produced from the conventional and renewable resources. The data of the electricity generation before the pandemic time have been considered and matched with the current situation. It has been observed that the energy production and consumption status of the Türkiye are varied during the pandemic time. For instance, the amount of some renewable resources in energy production decreases or increases. In addition to this, when the tables are examined, it can be seen that all the sources have a seasonal characteristic.

In this paper, the forecasting study on the monthly electricity generation of Türkiye using the data between years of the 2001 and 2020 has been done. Firstly, time series data of the all energy generation sources have been modelled and classified as a Simple Seasonal model, Winters' Multiplicative model, Winters' Additive model and *SARIMA(0,1,0)X(0,1,1)* model. After that, the forecasting process is implemented using the time series data and models. According to forecasting scenario, in 2021, the electricity generation shows different attitudes with regard to resources used.

According to the forecasting scenario in 2021, the electricity generation shows different attitudes with regard to the resources used. In 2022, especially increasing trends are expected for wind, biogas, natural gas, imported coal and fuel oil, whereas diesel and mineral coal are expected to be decreased in Türkiye.

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Appendixes

Table 1. Time series models of the monthly series of electricity generation data obtained from 2001 and 2020.

Model Description		
Model ID		Model Type
Gross generation (GWh)	Model_1	Winters' Multiplicative
Natural Gas	Model_2	Simple Seasonal
Hydro	Model_3	Simple Seasonal
Biogas Waste	Model_4	Winters' Additive
Geothermal	Model_5	SARIMA(0,1,0)X(0,1,1)
Wind	Model_6	Winters' Multiplicative
Solar	Model_7	Winters' Multiplicative
Fuel Oil	Model_8	Winters' Multiplicative
Diesel	Model_9	Simple Seasonal
Mineral coal	Model_10	Simple Seasonal
Imported coal	Model_11	Winters' Multiplicative
Asphalted	Model_12	Simple Seasonal
Lignite	Model_13	Simple Seasonal

Table 2. Model Fit statistics for time series models of the monthly series of electricity generation data obtained from 2001 and 2020

Model	Model Fit statistics	
	Stationary R-squared	MAPE
GrossgenerationGWh-Model_1	0.268	2.482
NaturalGas-Model_2	0.390	8.988
Hydro-Model_3	0.446	12.803
BiogasWaste-Model_4	0.348	12.237
Geothermal-Model_5	0.274	13.946
Wind-Model_6	0.677	18.788
Solar-Model_7	0.581	14.576
FuelOil-Model_8	0.557	17.980
Diesel-Model_9	0.633	10198.547
Mineralcoal-Model_10	0.524	11.324
Imported coal -Model_11	0.460	19.923
Asphalted -Model_12	0.589	50.051
Lignite-Model_13	0.499	7.668

Table 3. Estimation Value of Exponential Smoothing Model Parameters for monthly series of electricity generation data obtained from 2001 and 2020

Model		Estimate	SE	t	Sig.
GrossgenerationGWh-Model_1	Alpha (Level)	0.433	0.050	8.675	0.000
	Gamma (Trend)	0.001	0.031	0.032	0.974
	Delta (Season)	0.570	0.095	5.973	0.000
NaturalGas-Model_2	Alpha (Level)	0.700	0.062	11.231	0.000
	Delta (Season)	7.695E-5	0.057	0.001	0.999
Hydro-Model_3	Alpha (Level)	0.999	0.065	15.309	0.000
	Delta (Season)	6.687E-5	16.431	4.070E-6	1.000
BiogasWaste-Model_4	Alpha (Level)	0.655	0.052	12.561	0.000
	Gamma (Trend)	0.052	0.025	2.118	0.035
	Delta (Season)	0.990	0.192	5.148	0.000
Wind-Model_6	Alpha (Level)	0.100	0.002	39.985	0.000
	Gamma (Trend)	0.197	0.016	12.513	0.000
	Delta (Season)	0.001	0.001	0.815	0.416
Solar-Model_7	Alpha (Level)	0.334	0.011	29.428	0.000
	Gamma (Trend)	0.327	0.021	15.540	0.000
	Delta (Season)	0.139	0.021	6.662	0.000
FuelOil-Model_8	Alpha (Level)	0.799	0.064	12.506	0.000
	Gamma (Trend)	1.108E-5	0.009	0.001	0.999
	Delta (Season)	6.566E-5	0.028	0.002	0.998
Diesel-Model_9	Alpha (Level)	0.100	0.029	3.479	0.001

	Delta (Season)	2.028E-5	0.033	0.001	1.000
Mineralcoal -Model_10	Alpha (Level)	0.600	0.061	9.840	0.000
	Delta (Season)	2.938E-5	0.070	0.000	1.000
Importedcoal_Model_11	Alpha (Level)	0.301	0.036	8.249	0.000
	Gamma (Trend)	0.001	0.008	0.128	0.898
	Delta (Season)	0.072	0.009	7.734	0.000
Asphalted -Model_12	Alpha (Level)	0.600	0.082	7.293	0.000
	Delta (Season)	0.000	0.091	0.001	0.999
Lignite-Model_13	Alpha (Level)	0.700	0.064	10.984	0.000
	Delta (Season)	3.514E-5	0.082	0.000	1.000

Table 4. Estimation Value of ARIMA (0,1,0) (0,1,1) Model for monthly series of electricity generation data obtained from 2001 and 2020

Model				Estimate	SE	t and Sig.
		Difference		1		
Geothermal-Model_5	Square Root	Seasonal Difference		1		
		MA, Seasonal	Lag 1	0.576	0.058	9.910 and 0.00

Table 5. Forecasts Values for monthly series of electricity generation data obtained from 2001 and 2020

Model		Jan 2021	Feb 2021	Mar 2021	Apr 2021	May 021	Jun 2021	Jul 2021	Aug 021	Sep 2021	Oct 2021	Nov 021	Dec 2021
GrossgenerationGWh-Model_1	Forecast	28203.14	25495.65	26331.99	24092.58	25456.89	26733.62	31594.14	30858.60	27934.27	26024.21	26236.94	28359.91
	UCL	29543.98	26935.14	27896.45	25711.52	27214.34	28627.56	33775.34	33079.58	30086.87	28155.59	28455.12	30773.81
	LCL	26862.30	24056.15	24767.53	22473.64	23699.44	24839.68	29412.95	28637.63	25781.66	23892.83	24018.76	25946.00
	Forecast	8290.93	7428.17	7524.78	6961.30	6941.99	7444.86	8837.77	8965.22	8633.33	8404.97	8571.46	8780.35
NaturalGas-Model_2	UCL	9826.41	9302.46	9685.39	9374.50	9583.74	10296.90	11885.62	12197.04	12039.20	11976.43	12301.14	12661.82
	LCL	6755.46	5553.88	5364.16	4548.10	4300.24	4592.82	5789.92	5733.39	5227.45	4833.52	4841.77	4898.88
	Forecast	4263.74	3977.88	4943.90	5452.57	5408.76	4631.62	4764.74	4524.90	3508.49	3175.11	3235.09	3954.08
Hydro-Model_3	UCL	5603.08	5871.04	7262.15	8129.23	8401.20	7909.57	8305.24	8309.79	7522.92	7406.64	7673.12	8589.41
	LCL	2924.41	2084.72	2625.65	2775.91	2416.31	1353.67	1224.23	740.00	-505.94	-1056.43	-1202.94	-681.26
	Forecast	535.86	514.78	552.61	547.38	560.10	539.36	561.85	562.94	565.10	579.74	591.24	600.21
BiogasWaste-Model_4	UCL	549.64	531.52	572.09	569.49	584.76	566.52	591.48	595.04	599.66	616.77	630.74	642.20
	LCL	522.07	498.05	533.13	525.28	535.45	512.20	532.21	530.83	530.53	542.71	551.74	558.22
	Forecast	973.55	898.99	970.05	928.22	917.25	865.03	843.00	853.66	870.25	963.75	1016.76	1062.45
Geothermal-Model_5	UCL	1034.74	982.59	1076.71	1049.11	1051.97	1008.79	996.70	1019.31	1047.93	1160.86	1229.24	1289.48
	LCL	913.75	818.19	867.58	812.92	789.50	729.63	699.08	699.18	705.14	780.61	819.63	852.18
	Forecast	2205.26	2252.21	2150.41	1602.14	1499.47	1546.87	2443.90	2850.83	2126.16	1580.72	2239.19	2628.60
Wind-Model_6	UCL	2508.62	2557.80	2458.44	1910.10	1809.87	1861.98	2787.73	3222.65	2478.63	1918.65	2623.38	3057.95
	LCL	1901.91	1946.62	1842.38	1294.19	1189.06	1231.75	2100.06	2479.01	1773.70	1242.80	1855.00	2199.24
	Forecast	590.31	795.48	1141.23	1366.31	1528.45	1605.35	1820.84	1729.55	1550.08	1280.07	991.34	721.73
Solar-Model_7	UCL	680.79	900.11	1281.57	1548.94	1756.19	1872.49	2153.68	2078.06	1892.44	1589.77	1255.32	936.65
	LCL	499.84	690.85	1000.89	1183.68	1300.71	1338.20	1487.99	1381.04	1207.72	970.37	727.36	506.82
	Forecast	21.82	15.31	11.77	7.27	3.39	.59	-2.63	-6.17	-9.17	-12.89	-17.48	-23.80
FuelOil-Model_8	UCL	130.40	147.46	170.58	176.58	175.17	193.74	237.97	257.07	257.27	275.66	303.05	345.91
	LCL	-86.75	-116.84	-147.04	-162.04	-168.38	-192.55	-243.22	-269.40	-275.60	-301.45	-338.01	-393.51
	Forecast	82.65	62.21	-17.59	-20.03	-20.15	-19.92	-18.77	-18.06	-18.88	-20.15	-6.26	54.58
Diesel-Model_9	UCL	242.10	222.45	143.44	141.79	142.45	143.46	145.39	146.87	146.82	146.32	160.97	222.56
	LCL	-76.80	-98.04	-178.63	-181.85	-182.76	-183.30	-182.93	-182.99	-184.58	-186.61	-173.48	-113.40
	Forecast	318.03	290.53	313.44	284.13	293.12	315.33	342.35	340.86	316.65	315.86	315.43	337.51
Mineral-coal-Model_10	UCL	390.11	374.58	407.96	388.08	405.71	435.93	470.48	476.08	458.62	464.28	470.01	498.03
	LCL	245.95	206.47	218.91	180.18	180.54	194.72	214.23	205.63	174.67	167.45	160.84	176.99
	Forecast	5887.12	5181.13	4793.15	3532.12	4386.60	5287.42	6177.88	6331.79	5947.12	5906.58	5924.79	6084.58
Importedcoal_Model_11	UCL	6487.01	5801.58	5432.61	4167.66	5077.46	6046.64	7013.21	7195.81	6799.96	6773.74	6810.48	7000.53
	LCL	5287.23	4560.69	4153.69	2896.58	3695.73	4528.19	5342.55	5467.77	5094.28	5039.43	5039.10	5168.63
	Forecast	145.90	139.63	149.14	130.05	150.96	143.14	153.66	163.14	155.07	134.09	148.14	157.97
Asphalted -Model_12	UCL	210.99	215.54	234.51	223.92	252.64	252.05	269.37	285.25	283.28	268.11	287.74	302.93
	LCL	80.80	63.72	63.77	36.17	49.29	34.23	37.96	41.02	26.87	.07	8.55	13.02
	Forecast	3519.58	3192.89	3197.03	2787.98	2969.66	3291.54	3549.72	3563.38	3250.63	3324.89	3332.26	3672.28
Lignite-Model_13	UCL	4056.27	3847.99	3952.19	3631.41	3892.97	4288.34	4614.95	4692.91	4440.99	4573.11	4635.79	5028.85
	LCL	2982.88	2537.79	2441.87	1944.54	2046.35	2294.73	2484.48	2433.84	2060.26	2076.66	2028.73	2315.70

For each model. forecasts start after the last non-missing in the range of the requested estimation period. and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period. whichever is earlier.

Table 6. Diagnostic Checking of the Estimated Models.

Model	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
	Stationary R-squared	MAPE	Statistics	DF	Sig.	
GrossgenerationGWh-Model_1	0.268	2.482	30.083	15	0.012	0
NaturalGas-Model_2	0.390	8.988	39.139	16	0.001	0
Hydro-Model_3	0.446	12.803	32.325	16	0.009	0
BiogasWaste-Model_4	0.348	12.237	34.888	15	0.003	0
Geothermal-Model_5	0.274	13.946	19.121	17	0.322	0
Wind-Model_6	0.677	18.788	81.077	15	0.000	0
Solar-Model_7	0.581	14.576	60.758	15	0.000	0
FuilOil-Model_8	0.557	17.980	20.311	15	0.160	0
Motorin-Model_9	0.633	10198.547	45.309	16	0.000	0
TasKomur-Model_10	0.524	11.324	32.889	16	0.008	0
IthalKomur-Model_11	0.460	19.923	62.771	15	0.000	0
Asfaltit-Model_12	0.589	50.051	23.566	16	0.099	0
Linyit-Model_13	0.499	7.668	33.795	16	0.006	0