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Impact of the COVID-19 lockdowns on electricity and natural gas consumption in the different industrial zones and forecasting consumption amounts: Turkey case study

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ABSTRACT

The COVID-19 lockdowns have adversely affected the national economies and caused fluctuations in the energy industry. This study examined how the lockdowns during the COVID-19 pandemic affected the amount of electricity and natural gas consumption in four organized industrial zones in the Turkey. A significant decrease was observed in electricity and natural gas consumption amounts in April and May when lockdowns were also applied in four industrial zones. In April, electricity consumption decreased between 72 and 43%, and natural gas consumption decreased between 77 and 57%. In May, electricity consumption decreased between 60 and 32%, and natural gas consumption decreased between 69 and 45%. These decreases in industrial zones show that the economy has been significantly affected. Furthermore, in this study, Auto-Regressive Integrated Moving Average (ARIMA) and Holt-Winters models were developed to predict electricity and natural gas consumption of an industrial zone. ARIMA(0,0,2)(2,1,0)\(_7\) and ARIMA(0,0,2)(0,1,1)\(_7\) models were chosen as the best model for the electricity and natural gas consumption data respectively with a minimum MAPE of Electricity was 1.37%, RMSE of Electricity was 87.2, R\(^2\) of Electricity was 0.99, MAPE of Gas was 5.42% and RMSE of Gas was 50.9, R\(^2\) of Gas was 0.92.

Electricity and natural gas consumption was forecasted for the next ten days (10–19 March 2021) according to ARIMA models with 80% and 95% confidence intervals. In addition, in this study, the impact of low energy usage in the industrial zone due to the COVID-19 lockdowns on model prediction performance was also examined. The obtained results showed that the COVID-19 lockdowns were reduced the ARIMA model prediction accuracy.

1. Introduction

Coronavirus disease 2019 (COVID-19) is an acute respiratory disease caused by another new coronavirus (SARS-Cov-2) [1]. The pandemic spread to 185 countries in just four months. The coronavirus infected more than 100 million people and death more than 2.2 million people in one year [2]. Countries have implemented different strategies to prevent the spread of the virus, but lockdowns have become the inevitable end for all countries. This has affected economies globally [3]. Developments in the country’s economy affect electricity and natural gas consumption directly or indirectly. When positive economic developments are experienced, an increase occurs in the energy consumption of industrial sectors.

Electrical energy is one of the most needed energy types worldwide and it is a reflection of the development in an economy. The consumption amount of this type of energy increases every day due to the fact that electricity can be produced from many energy sources, it does not cause any harm to the environment, its area of use is wide, the population increases, and the technology advances.

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Natural gas provides a high economic value and is considered a strategic fuel type. The main reason for this is that it is consumed as an indirect energy source in the industry, i.e., as electrical energy generation. Countries like Turkey, which are poor in natural gas deposits, are...
dependent on foreign supplies. Therefore, it is very important for the country’s economy to use the natural gas both imported and supplied within the country efficiently and estimate its demand correctly.

An investigation of changes in energy consumption during the lockdowns in the COVID-19 pandemic has gained an upward momentum.

Ruan et al. [5], analyzed the impact of COVID-19 on the US electricity sector. In the entire US market, a decrease of 6.36–10.24% in April and 4.44–10.71% in May was observed in electricity consumption. It has been reported that a decrease in electricity consumption is associated with the increase in the number of COVID-19 cases and the duration of stay-at-home. Prol and Sungmin [6], examined the effect of COVID-19 on electricity consumption in the EU countries and USD states. In the study, it was observed that electricity consumption decreased by 3–12% in 5 months and most countries/states reached the baseline levels by the end of July. Agdas and Barooah [7], examined electricity data for three states in the USA until the end of May. In the study, it was observed that electricity demand decreased significantly during the pandemic. In the study, energy consumption was also estimated using the weather data for that period. Elavarasan et al. [8], reported that the domestic electricity load demand increased from 23% to 36% and the industrial load decreased from 42% to 32.34% in India. Leach et al. [9], examined the impact of the COVID-19 pandemic on electricity markets for some regions in Canada due to the difficulty accessing the dataset. In the study, it was observed that the electricity demand decreased by approximately 10% in Ontario and approximately 5% in Alberta, British Columbia, and New Brunswick. Supply decreases were observed at some natural gas facilities in the Alberta region. Furthermore, daily, weekly, and annual electricity demand was forecasted using the regression model in the study. Carvalho et al. [10], examined the impact of the COVID-19 pandemic on the electricity consumption models and consumption of Brazil between January 1 and May 27, 2020. Electricity consumption varied by region, and while a decrease of 7% was observed in the residential area, a decrease of 20% to 27% was observed in the commercial area. Santiago et al. [11], stated that the electricity demand in Spain decreased by 13.49% due to the COVID-19 bans and CO2 emissions decreased by 32.61% in comparison with the previous years. Halbrügge et al. [12], analyzed the effects of the COVID-19 outbreak on the electricity sector in Germany and European countries. It was seen that with the beginning of COVID-19 lockdowns, electricity consumption decreased in Germany, France, Italy, Spain, and Sweden compared to previous years. Ruan et al. [13], examined the impact of the COVID-19 outbreak on power system security, electrical power generation, electrical energy demand, and electricity prices in the USA. The results of the study showed that electricity energy demand and electricity prices decreased during the COVID-19 pandemic. Bahmanyar et al. [14], examined how different COVID-19 lockdowns imposed by European countries affect the electricity consumption profile. In the study, it was determined that different lockdown measures and their population activities in countries significantly changed the electricity consumption profile. Badesa et al. [15], analyzed the challenge of stability in the British electricity system during the COVID-19 lockdown and the future costs of stabilization actions in Great Britain. Jiang et al. [16], investigated the effects and challenges of COVID-19 pandemics on energy demand and consumption. In general, the regional effects of the COVID-19 epidemic were examined in the study. There are almost no studies specific to industrial zones that affect the economies of the country.

This study presents the following contributions:

- To examine the effect of the COVID-19 lockdown on electricity and natural gas consumption amount in four different industrial zones in Turkey;

- Comparison of the prediction performance of the ARIMA and Holt-Winters models in estimating electricity and natural gas consumption;
- Forecasting the electricity and natural gas consumption for the next ten days with the selected best-fitted model at 80–95% confidence intervals;
- To examine the impact of decreases in electricity and natural gas consumption amount due to the COVID-19 lockdowns on model prediction performance.

2. Materials and methods

In this section, data collection, the models used and evaluation metrics are introduced.

2.1. Data collection

In this study, electricity and natural gas consumption data for the four organized industrial zones in Turkey were used. Information on the organized industrial zones where the dataset was collected is presented in Table 1.

This study, it was examined how the electricity and natural gas consumption amounts in four industrial zones were affected by the COVID-19 lockdown. Furthermore, the future consumption amounts were forecasted for the first industrial zone, including daily electricity and natural gas consumption amounts. The dataset collected from Zone 1 includes daily electricity and natural gas consumption amounts for 373 days (02 March 2020–09 March 2021). To develop the ARIMA and Holt-Winters models, dataset were divided into training and test sets. The last month of the dataset was used to test models prediction performance. The other part was used for models learning. Electricity and natural gas consumption amounts were forecasted with the selected best-fitting model for the next ten days (10–19 March 2021) with 80% and 95% confidence interval. R programming language was used for the model development and analysis.

2.2. ARIMA model

ARIMA, also known as the Box-Jenkins model, is a statistical approach commonly used for time series analysis and forecasting. The main purpose of time series analysis is to reveal reliable and important statistics and use this information to predict the future values of the series. Time series components consist of trend, seasonal variations, cyclic variations, and random or irregular movements categories. Creating an ARIMA model for any time series dataset can be explained in four steps:

Data Stabilization: The first condition of modeling is to stabilize the time series. If the time series contains fluctuations such as a particular trend or seasonality, the relevant series is not stable. In other words, it will not be possible to express them with a mathematical model by looking at the past and future structures of the series. In order for the series to be modeled appropriately, they must first be made stable. If the observation values of a time series are not stable around the average

| Study area                      | Abbreviation          | Area (ha) | Enterprises | Employees |
|--------------------------------|-----------------------|-----------|-------------|-----------|
| Çerkezköy Organized Industrial Zone [18] | Zone 1              | 1273      | 270         | 77.000    |
| Bursa Organized Industrial Zone [19] | Zone 2              | 670       | 330         | >77.000   |
| Demirci Organized Industrial Zone [20] | Zone 3              | 485       | 542         | 45.000    |
| Nilüfer Organized Industrial Zone [21] | Zone 4              | 234       | 320         | 22.000    |
value of this series, stability is achieved by taking the differences of the series at the appropriate degree. The degree of taking a difference is symbolized by d.

Parameter Forecasting: The ARIMA model is usually shown as ARIMA (p,d,q), and the seasonal ARIMA model is shown as ARIMA(p,d,q)(P,D,Q). The process of selecting the most suitable (p, d, q) structure in the ARIMA model is called the model identification (determination). Here, p is the autoregressive model (AR) order, d is the degree of difference, q is the moving average (MA) model order. For the seasonal part of the ARIMA model, m shows the number of periods, P, D, and Q show the seasonal autoregressive, seasonal differencing, and seasonal moving average terms, respectively [22].

After the series is stabilized, the time series transforms into the ARMA(p,q) model. The AR(p), MA(q), and ARMA(p,q) models are given in Eqs. (1), (2), (3), respectively.

\[ y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \]  \hspace{1cm} (1)

\[ y_t = \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \]  \hspace{1cm} (2)

\[ y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \]  \hspace{1cm} (3)

Here, \( y_t \) shows the real value of the examined variable at time t, \( \phi \) indicates the autoregressive, \( \theta \) indicates the moving average parameter, \( \varepsilon_t \) indicates the random error at time t [23].

The autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs of the series are used to determine the order of the AR and MA terms. The ACF graph explains the relationship between the present value of the time series and the past values (1-unit past, 2-unit past, ..., n-unit past). In the graph, the x-axis refers to the correlation coefficient, and the y-axis refers to the number of lags. The PACF graph explains the partial correlation between the series and its lags.

Model Selection: After the data are stabilized, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the d-order difference sequence are calculated, and the best forecasting model is found. The AIC and BIC measure the goodness of fit of the model by considering the number of terms in the model. The smallest AIC and BIC value gives the most suitable model for estimation [24]. The AIC and BIC values of a model calculated as below:

\[ AIC(M_k) = -2 \log L(M_k) + 2k \]  \hspace{1cm} (4)

\[ BIC(M_k) = -2 \log L(M_k) + \log(n)k \]  \hspace{1cm} (5)

The monthly total electricity consumption of four industrial zones for 2020 in Turkey.

![Fig. 1. The monthly total electricity consumption of four industrial zones for 2020 in Turkey.](image)

\[ L(M_k) \] is the probability corresponding to the \( M_k \) model, n is the number of the measurements recorded, and k is the number of the parameters forecasted.

Validation and Evaluation: The predictive performance of the models were compared using the evaluation metrics presented in Section 2.4.

2.3. Holt-Winters model

The Holt-Winters (HW) model was proposed by Chatfield in 1988 and is suitable for short-term forecasting [25]. HW predicts with high precision in time series data that includes both trend and seasonality. It uses the maximum likelihood function to estimate parameters. HW include two models: Additive and Multiplicative models. The multiplicative models are applied if the seasonal effect shows a steady increase or decrease with the trend. The additive models are used when data with trend and seasonality don’t increase over time. In this study, the additive model was used for electricity and natural gas estimation. The HW model consists of level, trend and seasonality components. It allows to control these components for prediction. These components are mathematically expressed as in Eqs. (6), (7), (8), respectively.

\[ Level: \quad L_t = \alpha (a_t - S_{t-p}) + (1 - \alpha)(L_{t-1} + b_{t-1}) \]  \hspace{1cm} (6)

\[ Trend: \quad b_t = \beta (L_t - L_{t-1}) + (1 - \beta)b_{t-1} \]  \hspace{1cm} (7)

\[ Seasonal: \quad S_t = \gamma (a_t - L_t) + (1 - \gamma)S_{t-p} \]  \hspace{1cm} (8)

The forecast is mathematically expressed as in Eq. (9) and its obtained from level, trend and seasonality.

\[ Forecast: \quad F_{t+m} = L_t + b_m + S_{t-p} + m \]  \hspace{1cm} (9)

\( \alpha, \beta \) and \( \gamma \) constant are the smoothing parameters of level, trend, and seasonal, respectively. \( L_t \) is the estimate of the level, \( b_t \) is the estimate of the slope and \( a_t \) is the actual value of the series at time t. \( S_t \) is seasonal component, p is number of seasons in a year and m is the number of periods to be forecast.

2.4. Model evaluation

The metrics presented in this section were used to measure of goodness of fit of the models. A model accuracy is measured by comparing the actual values with the estimated values. The Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and coefficient of determination (\( R^2 \)) values were calculated to test the
predictive accuracy of the models. These metrics are mathematically expressed in Eqs. (10), (11), (12), respectively.

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{e_i}{\text{actual}_i} \right| \times 100
\]  

\[RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (e_i)^2}
\]  

\[
R^2 = 1 - \frac{\text{sum of squares of residuals (SS}_{\text{res}})}{\text{total sum of squares (SS}_{\text{tot}})}
\]  

Fig. 2. The monthly total natural gas consumption of four industrial zones for 2020 in Turkey.

Fig. 3. Box plot of the (a) electricity and (b) natural gas consumption by month for 2020.
Here, $n$ is the number of observations, $\text{actual}_t$ is the actual value at time $t$, $e_t$ is the error ($\text{actual}_t - \text{predicted}_t$) at time $t$.

The lower MAPE and RMSE values indicate the more accurate prediction results. MAPE expresses prediction errors as a percentage, and estimating models with MAPE values below 10% have a high degree of accuracy [26]. MAPE is a good criterion to compare models because it does not depend on the scale and unit of the data [27]. $R^2$ lies between 0% and 100%. $R^2$ value of 100% means the model explains all the variation of the target variable. $R^2$ value of 0% measures zero predictive power of the model. The higher the $R^2$, the better model estimate.

3. Experimental results

The monthly total electricity consumption of four industrial zones in Turkey are presented in Fig. 1. A significant decrease in consumption amounts was observed in April and May when lockdowns were implemented in four industrial zones. In the following months, when there were no bans, consumption amounts reached the baseline levels.

While the total electricity consumption amount for the first industrial zone was 139.6 GWh in March, the total consumption decreased to 79.7 GWh and 95.2 GWh, respectively, in April and May when the lockdowns were imposed. The total electricity consumption amount decreased by 43% and 32% in April and May, respectively (compared to March). Electricity consumption in the second industrial zone was 132.8 GWh in March, 56.3 GWh in April and 69.0 GWh in May. In this zone, in April and May, the total electricity consumption decreased by 58% and 48%, respectively. The total electricity consumption amount in the third industrial zone in March, April, and May was 92.6 GWh, 26.3 GWh, and 37.4 GWh, respectively. The total electricity consumption decreased by 72% and 60% in April and May, respectively. The total electricity consumption amount in the fourth zone in March, April, and May is 27.5 GWh, 13.3 GWh, and 15.1 GWh, respectively. Electricity consumption decreased by 52% and 45% respectively in April and May. Electricity consumption decreased by 52% in April and 45% in May. The reason for the decrease in the amount of electricity consumption in April compared to May is the more frequent implementation of lockdowns. With the end of lockdowns, the total electricity consumption amounts reached the baseline levels.

The monthly total natural gas consumption amounts of four industrial zones in Turkey are presented in Fig. 2. A significant decrease was observed in natural gas consumption amounts in April and May when lockdowns were implemented in four industrial zones, as in electricity consumption amounts. In other months when there were no restrictions, consumption amounts reached normal levels.

The total natural gas consumption amount in the first industrial zone in March, April, and May was 18.008, 7.831, and 9.840 $10^3$SM3, respectively. The natural gas consumption amount decreased by 57% and 45% in April and May, respectively, when lockdowns were implemented (compared to March). The total natural gas consumption in March, April and May in the second industrial zone was 14.409, 5.352, 5.819 $10^3$SM3, respectively. In this industrial zone, natural gas consumption decreased by 63% and 60% in April and May, respectively. The total natural gas consumption in the third industrial zone in March was 13.447, April was 3.086, and May was 4.202 $10^3$SM3. Natural gas consumption decreased by 63% and 60% in April and May, respectively. The total natural gas consumption in the third industrial zone in March was 13.447, April was 3.086, and May was 4.202 $10^3$SM3. Natural gas consumption decreased by 77% and 69% in April and May, respectively, compared to March. The total natural gas consumption in the fourth industrial zone was
1.748 in March, 652 in April and 731 in May, and the consumption decreased by 63% and 58% in April and May, respectively.

The distribution of electricity and natural gas consumption by months for the first industrial zone is presented in Fig. 3 with the Box-Whisker graph. When Fig. 3(a) is examined, it is observed that the average electricity consumption amounts reached the lowest levels in April and May (2657 MWh, 3071 MWh, respectively). In May, when the lockdown was more partial, it is observed that the data spread to a wide range, in other words, there was more deviation in daily electricity consumption amounts. In April, when curfews were applied more frequently, the standard deviation was lower. In April, the highest electricity consumption amount was 3603 MWh, and the lowest consumption amount was 1203 MWh. In May, the highest electricity consumption amount was 4509 MWh, and the lowest consumption amount was 846 MWh. These consumption amounts are at very low levels compared to other months without curfew.

As seen in Fig. 3(b), the monthly average natural gas consumption arrived at the lowest levels in April and May (253 $10^3$Sm$^3$, 331 $10^3$Sm$^3$, respectively). In April, the highest consumption was 414.3 $10^3$Sm$^3$ and the lowest consumption was 98.9 $10^3$Sm$^3$. In May, the highest consumption was 542.1 $10^3$Sm$^3$ and the lowest consumption was 78.9 $10^3$Sm$^3$. It is observed that the deviation in natural gas consumption amounts was more significant in May when partial lockdowns were imposed, compared to April.

Another aim of this study is to determine the most successful one of the ARIMA and Holt-Winters models and to make a future prediction. In order to determine the optimal ARIMA models, firstly, the direction of daily electricity and natural gas consumption data should be examined, the stationarity and seasonality of the series should be determined. Times series graphs for electricity and natural gas consumption are presented in Fig. 4.

When the electricity and natural gas consumption series in Fig. 4 is examined, a decrease in energy consumption is observed in April and May, when there were lockdowns. The decrease in energy consumption in first of Jan is due to the Christmas holiday. In the other months, there is an increasing trend in general, and it is observed that consumption decreases suddenly as there is no work in the industry on Sundays. The fact that the usage level of the series reaches the lowest value every week indicates that there is seasonality in the series. Furthermore, it is observed that both the electricity and natural gas series are non-stationary. The ACF and PACF graphs of the original electricity and natural gas consumption time series are given in Fig. 5.

When the ACF graph of the electricity and natural gas series is examined given in Fig. 5, it is observed that the autocorrelation coefficient decreases very slowly towards zero and the increasing lag length indicates that the series are non-stationary. On the other hand, the sinus fluctuation in the ACF graph indicates that the seasonal effect exists. It is observed that the seasonality period in the ACF graphs is 7. Moreover, it is observed that the 7th and 14th lags are outside the limits in the PACF graphs. This also shows that the seasonal frequency is weekly.

When the ACF and PACF graphs are evaluated together, it is observed that the electricity and natural gas series are non-stationary. Non-stationary understood observationally was subjected to the unit root test analysis to be evaluated in light of real data. The results of the Augmented Dickey-Fuller (ADF) test applied to the original series are given in Table 1. In the ADF test, the null hypothesis states that the series given is unit root, in other words, the series is non-stationary, while the

| Data                        | ADF Test | Significance | Stationarity |
|-----------------------------|----------|--------------|--------------|
| Original series of electricity | -2.252   | 0.469        | Non-Stationary |
| Original series of natural gas | -2.589   | 0.328        | Non-Stationary |

Fig. 5. ACF and PACF plots of the original series (a) electricity and (b) natural gas consumption.

Table 2
The results of the ADF unit root test for original series.
alternative hypothesis states that the series is stationarity. Therefore, we want to reject the null hypothesis. In this study, the significance level was selected as 0.01 in order to reject the null hypothesis with 99% confidence. In other words, to reject the null hypothesis, the $P$-value should be $\leq 0.01$. To ensure that the original electricity and natural gas series were non-stationary, the ADF unit root test analysis was applied to the original series, and the results are presented in Table 2.

When the ADF test results of the original series are examined, for both electricity and natural gas series were $P > 0.01$. Since seasonal fluctuation is observed in the ACF and PACF graphs of the original series in Fig. 5, firstly, the seasonal difference is taken to stabilize both the electricity and natural gas time series. The graphs of the seasonally adjusted series are presented in Fig. 6. When Fig. 6 is examined, it is observed that the seasonally adjusted series becomes stationarity. When ACF and PACF were analyzed after taking a seasonal difference, it was observed that autocorrelation and partial autocorrelations decreased

Table 3
The results of the ADF unit root test for seasonal differenced series.

| Data                          | ADF Test | Significance | Stationarity |
|-------------------------------|----------|--------------|--------------|
| Seasonal difference of electricity | -7.992   | $< 0.01$     | Stationary   |
| Seasonal difference of natural gas | -7.648   | $< 0.01$     | Stationary   |

![Fig. 6. Time series, ACF and PACF plot of the seasonal differenced series (a) electricity and (b) natural gas consumption.](image)

Table 4
Comparison of tested ARIMA models.

| Model                          | Electricity | Natural Gas |
|-------------------------------|-------------|-------------|
| AIC                           | BIC         | MAPE        | RMSE        | AIC         | BIC         | MAPE        | RMSE        |
| ARIMA(1,0,0)(0,1,1)$_T$       | 4323.5      | 4334.4      | 4.46%       | 248.7       | 3312.7      | 3327.8      | 10.78%      | 92.1        |
| ARIMA(2,0,0)(0,1,1)$_T$       | 4325.4      | 4340.1      | 4.40%       | 246.3       | 3305.8      | 3320.4      | 11.43%      | 97.0        |
| ARIMA(1,0,1)(0,1,1)$_T$       | 4328.4      | 4340.1      | 4.39%       | 245.9       | 3306.8      | 3321.4      | 11.66%      | 98.7        |
| ARIMA(2,0,1)(0,1,1)$_T$       | 4326.1      | 4344.4      | 4.46%       | 249.1       | 3310.4      | 3322.7      | 11.11%      | 95.2        |
| ARIMA(1,0,0)(2,1,0)$_T$       | 4363.0      | 4377.6      | 1.41%       | 92.5        | 3327.8      | 3347.9      | 6.12%       | 53.6        |
| ARIMA(1,0,2)(1,1,0)$_T$       | 4366.0      | 4387.9      | 1.86%       | 116.4       | 3337.0      | 3348.0      | 6.09%       | 51.4        |
| ARIMA(2,0,0)(2,1,0)$_T$       | 4378.1      | 4392.7      | 1.71%       | 108.5       | 3336.3      | 3350.9      | 6.77%       | 61.1        |
| ARIMA(0,0,3)(0,1,2)$_T$       | 4374.9      | 4396.9      | 3.95%       | 227.4       | 3340.0      | 3361.9      | 7.98%       | 71.6        |
| ARIMA(0,0,3)(0,1,1)$_T$       | 4380.4      | 4398.7      | 2.90%       | 175.6       | 3345.7      | 3364.0      | 5.54%       | 52.5        |
| ARIMA(0,0,3)(1,1,0)$_T$       | 4409.6      | 4427.9      | 1.58%       | 102.0       | 3359.6      | 3377.9      | 6.47%       | 58.7        |
| ARIMA(0,0,2)(0,1,2)$_T$       | 4414.2      | 4432.5      | 3.73%       | 218.1       | 3374.4      | 3392.7      | 6.74%       | 62.8        |
| ARIMA(0,0,2)(2,1,1)$_T$       | 4418.3      | 4432.9      | 2.45%       | 152.7       | 3377.0      | 3391.6      | 5.42%       | 56.9        |
| ARIMA(0,0,3)(0,1,0)$_T$       | 4454.7      | 4469.4      | 1.69%       | 114.5       | 3379.6      | 3394.3      | 8.32%       | 74.1        |
| ARIMA(0,0,2)(2,1,0)$_T$       | 4433.2      | 4451.5      | 1.37%       | 87.2        | 3381.8      | 3400.1      | 5.64%       | 51.9        |
natural gas consumption series were obtained. These models were compared according to RMSE and MAPE results and presented in Table 8. It is seen that the predicted values are very close to the actual values. The $R^2$ of the ARIMA(0,0,2)(1,0,1)$\_T$ model is 0.99. This means that the model can explain 99% of the variation observed in the series in forecasting the amount of electricity consumption. The $R^2$ of the ARIMA(0,0,2)(0,1,1)$\_T$ model is 0.92. In other words, the fit in forecasting the amount of natural gas consumption is 92%.

The ACF and PACF plots of the ARIMA models’ residuals given in Fig. 7. It is seen that the correlation values do not exceed the 0.05 significant boundary. In other words, the residual sequence does not contain non-random components.

Table 5

| Term      | Coefficient | SE    | $t$ statistic | P-value |
|-----------|-------------|-------|--------------|---------|
| MA(1)     | 0.906       | 0.051 | 17.67        | 0.000   |
| MA(2)     | 0.393       | 0.042 | 9.42         | 0.000   |
| SAR(1)    | -0.475      | 0.054 | -8.82        | 0.000   |
| SAR(2)    | -0.200      | 0.053 | -3.80        | 0.000   |

The estimated coefficients of ARIMA(0,0,2)(2,1,0)$\_T$ and corresponding standard errors, $t$ statistics and P-values.

Table 6

| Term      | Coefficient | SE    | $t$ statistic | P-value |
|-----------|-------------|-------|--------------|---------|
| MA(1)     | 0.716       | 0.055 | 13.05        | 0.000   |
| MA(2)     | 0.377       | 0.045 | 8.41         | 0.000   |
| SMA(1)    | -0.595      | 0.064 | -9.35        | 0.000   |

The estimated coefficients of ARIMA(0,0,2)(0,1,1)$\_T$ and corresponding standard errors, $t$ statistics and P-values.

depending on the number of lags and approached zero. This is a sign that the series is stationary.

The ADF test results of the seasonally differentiated electricity and natural gas series are given in Table 3. When the ADF test results of the series from which a seasonal difference was taken are examined, it shows that the electricity and natural gas consumption series do not contain a unit root, in other words, they become stationary ($P < 0.01$). Thus, the modeling stage can be started as the stability condition is met.

ACF and PACF are examined in order to determine the ARIMA model terms. Structure of these graphs is examined, it may sometimes not be possible to clearly observe the structure of the model. So, auto ARIMA was used to determine the ARIMA model parameters. Using this method, 192 ARIMA models for the electricity and 192 ARIMA models for the natural gas consumption series were obtained. These models were reduced to 15, according to the minimum AIC and BIC values (Table 4). In order to evaluate the prediction accuracy of these 15 ARIMA models and determine the most successful model, the last month of the dataset was estimated with ARIMA models. Models prediction performances were compared according to RMSE and MAPE results and presented in Table 4.

Among the ARIMA models presented in Table 4, the ARIMA model with minimum MAPE and RMSE values was determined to be the best-fitting model. Accordingly, ARIMA(0,0,2)(2,1,0)$\_T$ was determined as the best model for electricity consumption. The estimated coefficients, corresponding standard errors (SE), $t$-values, and $p$-values of the ARIMA (0,0,2)(2,1,0)$\_T$ model are given in Table 5.

The coefficient column shows the importance of each term. The negative sign of a coefficient indicates an inverse relationship between the term and the current value. The higher the absolute value of the coefficient is, the greater the effect of the variable on electricity consumption is. Standard error indicates the standard deviation of the coefficient. The smaller the standard error is, the more accurate the forecast will be. A more precise coefficient results in a more accurate electricity consumption model. The $p$-value indicates the importance of the weight of each term. Terms are significantly different from zero at the 95.0% confidence level ($P < 0.05$).

The estimated value of 0.906 for the moving average term (MA (1)) indicates that if the error in the previous timestamp increases by one, today’s electricity consumption increases by 0.906. If the error in the previous timestamp increases by two, today’s electricity consumption increases by 0.393 (MA (2)). The estimated value of $-0.475$ for the seasonal autoregressive term (SAR (1)) shows that if the value in the previous week increases by one, today’s electricity consumption will decrease by 0.475. SAR(2) $= -0.200$ shows that if the value in the previous week increases by two, it shows that today’s electricity consumption will decrease by 0.200.

According to Table 4, the ARIMA(0,0,2)(0,1,1)$\_T$ was determined as the best prediction model for the natural gas consumption amounts. The estimated coefficients, corresponding standard errors, $t$ statistics, and $p$-values of the ARIMA(0,0,2)(0,1,1)$\_T$ model are given in Table 6.

The estimated value of 0.716 for the moving average term (MA (1)) shows that if the error in the previous timestamp increases by one, today’s natural gas consumption increases by 0.716. If the error in the previous timestamp increases by two, today’s natural gas consumption increases by 0.377 (MA(2)). The estimated value of $-0.595$ for the seasonal moving average term (SMA (1)) shows that if the value in the previous week increases by one, today’s natural gas consumption will decrease by 0.595. Model terms are considerably different from zero at the 95.0% confidence level ($P < 0.05$).

Another time series method we use in the study is the Holt-Winters. As with the ARIMA model, also the Holt-Winters method was trained with the first eleven months of the dataset and the prediction accuracy was tested with the last one month. The comparative performance results of the ARIMA and Holt-Winters models for the prediction of electricity and natural gas consumption are given in Table 7.

Comparison results indicate that the ARIMA model is more successful than the Holt-Winters model for the prediction for electricity and natural gas consumption. After the most successful model was determined, the $R^2$ value was used to determine the degree of fit for the ARIMA models. Actual (test set) and predicted consumption with the ARIMA models are given in Table 8. It is seen that the predicted values are very close to the actual values. The $R^2$ of the ARIMA(0,0,2)(2,1,0)$\_T$ model is 0.99. This means that the model can explain 99% of the variation observed in the series in forecasting the amount of electricity consumption. The $R^2$ of the ARIMA(0,0,2)(0,1,1)$\_T$ model is 0.92. In other words, the fit in forecasting the amount of natural gas consumption is 92%.

The ACF and PACF plots of the ARIMA models’ residuals given in Fig. 7. It is seen that the correlation values do not exceed the 0.05 significant boundary. In other words, the residual sequence does not contain non-random components.

Daily electricity and natural gas consumption amounts for the next ten days (10 – 19 March 2021) were forecasted using the chosen ARIMA (0,0,2)(2,1,0)$\_T$ and ARIMA(0,0,2)(0,1,1)$\_T$ models. The forecast results are presented in Table 9 and Fig. 8. As seen in Fig. 8, it was determined that the forecast values adapted to the actual data group with the course followed. It is thought that this will provide a sufficient and consistent forecast.

The study also examining the effect of decreases in energy consumption due to the COVID-19 lockdowns on the ARIMA prediction performance. The amount of electricity (MWh) and natural gas (10$^6$SM$^3$) consumption with the COVID-19 lockdowns (marked red diamond) between 02 March 2020-09 March 2021 is given in Fig. 9. The first COVID-19 case in the Turkey was seen on 11 March 2020. Flexible and remote work started on 22 March and ended on 01 June 2020. It is seen that the consumption amounts reach the lowest values on these restriction days. Nevertheless, it is clearly seen in Fig. 9 that the consumption amounts in the period of working remotely and flexibly are lower than in other periods in this industrial zone.

As seen in Fig. 9, the COVID-19 lockdowns were caused a sharp decrease in energy usage. Since these low values distort the general trend in the series, they are defined as noise. Increase of the noise in the dataset decreases the model prediction success [28]. For the purpose of examining the effect of due to the COVID-19 lockdowns decreases in energy consumption in the model prediction performance, the simple
moving average (SMA) method was applied to reduce the noise levels in datasets. In the SMA method, the estimated observation value is calculated by taking the arithmetic mean of the neighboring data. In this paper, 7-days periods were used to reduce noise in the time-series datasets. Each forecast period, the newest observation is included and the oldest observation subtracted. The consumption values for the raw dataset and the smoothed dataset were prediction results are given in Table 10.

According to Table 10, it is seen that the decrease in consumption values caused by the COVID-19 affects the prediction performance of the model and the model makes estimation with higher error.

4. Conclusions

The COVID-19 pandemic affects the health systems of all countries, and a significant number of human deaths occur globally. The global health crisis is a tragedy, and the pandemic causes economic disruptions, and its impact is felt across energy systems. The COVID-19

| Table 8 | Comparison of actual vs predicted consumptions for test set. |
|----------|-------------------------------------------------------------|
| Electricity (MWh) ARIMA(0,0,2)(2,1,0) | Natural Gas ($10^3$ $\text{SM}^3$) ARIMA(0,0,2)(0,1,1) |
| Actual | Predicted | Actual | Predicted |
|---------|-----------|---------|-----------|
| 4659    | 4703      | 5510    | 5412      |
| 5392    | 5438      | 5526    | 5397      |
| 5453    | 5418      | 5524    | 5389      |
| 5469    | 5414      | 5374    | 5325      |
| 5251    | 5345      | 5137    | 5038      |
| 5076    | 5058      | 3367    | 3474      |
| 3503    | 3487      | 4671    | 4692      |
| 4685    | 4698      | 5357    | 5420      |
| 5544    | 5420      | 5388    | 5403      |
| 5579    | 5403      | 5431    | 5396      |
| 5573    | 5398      | 5255    | 5332      |
| 5517    | 5337      | 5029    | 5043      |
| 5149    | 5041      | 3468    | 3476      |
| 3551    | 3471      | 4684    | 4691      |
| 4730    | 4684      | 5444    | 5418      |

Fig. 7. ACF and PACF of residuals for ARIMA(0,0,2)(2,1,0) and ARIMA(0,0,2)(0,1,1).

| Table 9 | Forecasting electricity and natural gas consumption with 80% and 95% confidence interval (CI). |
|----------|---------------------------------------------------------------------------------------------|
| Date     | Electricity (MWh) ARIMA(0,0,2)(2,1,0) | Natural Gas ($10^3$ $\text{SM}^3$) ARIMA(0,0,2)(0,1,1) |
|          | Forecast | 80% CI | 95% CI | Forecast | 80% CI | 95% CI |
|----------|----------|--------|--------|----------|--------|--------|
| 10/03/2021 | 5477   | [4830,6123] | [4488,6466] | 833  | [723,942] | [665,1000] |
| 11/03/2021 | 5501   | [4629,6373] | [4168,6835] | 825  | [692,958] | [621,1029] |
| 12/03/2021 | 5340   | [4432,6248] | [3951,6729] | 766  | [627,904] | [553,1078] |
| 13/03/2021 | 5082   | [4174,5991] | [3693,6472] | 711  | [572,850] | [499,923] |
| 14/03/2021 | 3457   | [2548,4365] | [2067,4846] | 460  | [321,599] | [248,673] |
| 15/03/2021 | 4689   | [3781,5598] | [3300,6078] | 827  | [688,966] | [615,1039] |
| 16/03/2021 | 5433   | [4525,6341] | [4044,6822] | 838  | [699,977] | [626,1051] |
| 17/03/2021 | 5462   | [4493,6341] | [3980,6945] | 837  | [686,988] | [606,1067] |
| 18/03/2021 | 5486   | [4470,6563] | [3932,7041] | 822  | [666,979] | [583,1061] |
| 19/03/2021 | 5323   | [4298,6349] | [3755,6891] | 798  | [600,916] | [517,1000] |
pandemic causes instability in the global economy and significant variability in energy consumption levels. Energy consumption is a reflection of economic activity. Considering that electrical energy is mostly used in manufacturing industries/economies, its consumption is an indicator of economic fluctuations. The proportion of the industry in electricity consumption in Turkey is 35% in 2018, 41% in 2019, and 35% in 2020. The decreased in electricity consumption compared to the previous year indicates that the production was decreased due to the curfews.

The lockdowns imposed by countries to prevent the spread of the pandemic caused a significant reduction in energy consumption in the manufacturing industry. In this study, the change in electricity consumption amounts in April and May, when lockdowns were implemented in four different industrial zones, was examined. Significant decreases were observed in electricity consumption in all industrial zones examined in the study (see the result section). Briefly, electricity consumption decreased between 72 and 43%, and natural gas consumption decreased between 77 and 57% in April. In May, electricity consumption decreased between 60 and 32%, and natural gas consumption decreased between 69 and 45%. In other months when there were no bans, it was observed that consumption amounts reached baseline levels. These fluctuations in the amount of energy consumption create a financial problem for the energy sectors because it is known that a large part of the profit rate of the electricity sector companies is due to industrial, commercial, and traction load [8].

The energy demand in the world increases in parallel with the increasing population and industrialization rates. Since electrical energy is an energy type that cannot be stored, investment and capacity determination issues are important in this field. Especially for countries foreign-dependent in energy resources, it is very important to create a reliable forecasting model that can be a reference in forecasting consumption values and deciding on the amount of imports. The effective regulation of the balance between the production and consumption of energy resources provides significant financial gains for countries.

In this study, the prediction performance of the electricity and natural gas consumption amounts of the ARIMA and Holt-Winters models were compared and results indicated the ARIMA is the best-fitted model for estimation of energy consumption. The ARIMA(0,0,2)(2,1,0)\(_7\) model was chosen as the best model for the electricity consumption data with a MAPE of 1.37%, RMSE of 87.2, and the R\(^2\) value of the fit of 99%. The ARIMA(0,0,2)(0,1,1)\(_7\) model was chosen as the best model for the natural gas consumption data with a MAPE was 5.42%, RMSE was 50.9 and the R\(^2\) value of the fit was 92%. Using the determined ARIMA models, electricity and natural gas consumption amounts for the next ten days (10 – 19 March 2021) were forecasted with 80% and 95% confidence intervals.

Finally, the impact of decreases in electricity and natural gas consumption amount due to the COVID-19 lockdowns on the ARIMA model prediction performance was examined. It was observed that the model prediction performance was higher in electricity and natural gas consumption datasets where the effect of the COVID-19 was smoothed (Table 10). Thereby, it can be said that decreases in the amount of energy consumption due to the COVID-19 lockdowns were negatively affected the model prediction accuracy.
CRediT authorship contribution statement

Pınar Cihan: Software, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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