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Forecasting seasonal electricity generation in European countries under Covid-19-induced lockdown using fractional grey prediction models and machine learning methods

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**HIGHLIGHTS**

- A novel genetic algorithm-based seasonal fractional grey model is proposed.
- Monthly electricity generation is forecasted since the Covid-19 lockdown started.
- Seasonal grey and machine learning models are used for forecasting.
- The selected countries are France, Germany, Spain, Turkey, and the UK.
- The share of renewables in total electricity generation is forecasted.

**ABSTRACT**

Balances in the energy sector have changed since the implementation of the Covid-19 pandemic lockdown in Europe. This paper analyses how the lockdown affected electricity generation in European countries and how it will reshape future energy generation. Monthly electricity generation from total renewables and non-renewables in France, Germany, Spain, Turkey, and the UK from January 2017 to September 2020 were evaluated and compared. Four seasonal grey prediction models and three machine learning methods were used for forecasting; the quarterly results are presented to the end of 2021. Additionally, the share of electricity generation from renewables in total electricity generation from 2017 to 2021 for the selected countries was compared. Electricity generation from total non-renewables in the second quarter of 2020 for France, Germany, Spain, and the UK decreased by 21\%–25\% compared to the same period of 2019; the decline in Turkey was approximately 11\%. Additionally, electricity generation from non-renewables in the third quarter of 2020 for all countries, except Turkey, decreased compared to the same period of the previous year. All grey prediction models and support vector machine method forecast that the share of renewables in total electricity generation will increase continuously in France, Germany, Spain, and the UK to the end of 2021. The forecasting methods provided by...
1. Introduction

Since the World Health Organization (WHO) declared the coronavirus disease 2019 (Covid-19) a pandemic on March 11, there have been over 100 million confirmed cases and over 2 million confirmed deaths worldwide [1]. The implementation of lockdowns by governments in Europe in March changed habits in the energy sector [2]; the effects of Covid-19 on the energy sector have recently become a popular subject of research.

Elavarasan et al. [3] investigated the impact of Covid-19 on the energy and power sector in the USA, Italy, Australia, and India. Bahmanyar et al. [4] compared the impact of Covid-19 on electricity consumption in Belgium, Italy, the Netherlands, Spain, Sweden, and the UK. Roidt et al. [5] revealed changes in electricity generation and consumptive water footprint of thermal power plant operations in France, Germany, Italy, Spain, and Switzerland during the Covid-19 pandemic lockdown. Huang et al. [6] predicted the monthly electricity consumption gap in China during Covid-19. Sui et al. [7] found that ridership had a greater impact on energy consumption and emissions for transit buses and investigated the spatio-temporal emission characteristics of buses and potential change analysis on the emissions from buses caused by ridership reduction post-Covid-19. Zhang et al. [8] simulated how a lockdown would cause a market slowdown in the distributed PV sector in Japan. Santiago et al. [9] analysed the electricity demand in Spain during the Covid-19 pandemic (March 14 to April 30) and found that the electricity consumption had decreased by 13.5% compared to the average value of the five previous years. Additionally, the share of renewable energy increased during the lockdown. Jiang et al. [10] overviewed the impacts and challenges of Covid-19 on the energy demand and consumption and highlighted energy-related lessons and emerging opportunities. Rouleau and Gosselin [11] quantified the impacts of the Covid-19 lockdown on energy consumption (electricity, hot water, and space heating) in residential areas in Quebec City, Canada.

In general, the above-mentioned studies mostly analysed how the energy sector in European countries was affected by Covid-19; however, projections for the future on this subject are insufficient. Forecasting tools could be used to determine how Covid-19 will reshape the future of the energy sector in European countries.

Forecasting plays an important role for decision makers and can be helpful for predicting the future based on past data. One of the popular forecasting tools are the grey prediction models, of which the simplest form is GM(1,1), first proposed by Ju-Long Deng [15]. The advantage of GM(1,1) lies in its forecasting capability with relatively limited data [16]. However, GM(1,1) is only successful for data with exponential characteristics, and the prediction performance is insufficient in case of data fluctuations [17]. Wu et al. [18] first introduced a fractional order accumulation to improve GM(1,1)’s prediction accuracy. The fractional GM(1,1) model achieves better prediction performance than the traditional grey model by including the fractional derivatives parameter [19]. Fractional accumulated grey prediction models have been widely used to forecast carbon dioxide emissions in BRICS countries [20], the cumulative number of confirmed cases of COVID-19 in Italy, the UK, and the USA [21], precious metal content in electronic waste [22], short-term air quality predictions [23], and carbon emissions [24]. Many recent studies used fractional grey models in the energy sector to forecast the short-term renewable energy consumption in China [25], natural gas consumption of countries [26], annual electricity consumption in China [27], manufacturing industrial natural gas consumption in China [28], electricity consumption in India and China [29], electricity consumption in China [30], electricity generation and installed capacity of total renewable and hydro energy in Turkey [31], renewable energy consumption in France, Germany, Italy, Spain, Turkey, and the UK [32], and renewable energy consumption in the European countries [33]. The Bernoulli model (FANGBM(1,1)) is a fractional nonlinear grey prediction model based on the combined nonlinear grey Bernoulli model (NGBM(1,1)) and the rth accumulated generation operation (r-AGO) [25]. FANGBM(1,1) has been used to forecast the renewable energy consumption of China [25], electricity generation and installed capacity of total renewable and hydro energy of Turkey [31], cumulative number of confirmed cases of Covid-19 in various countries [21], and renewable energy consumption of European countries [32]. The above-mentioned studies predicted annual data. However, seasonal fluctuations should be considered for data with monthly changes (e.g., electricity generation and consumption) that depend on climatic conditions, such as temperature and the number of daylight hours [34]. The seasonal fluctuation method has been used with the GM(1,1) to forecast the electricity demand of South Australia [34], electricity consumption of primary industries in China [35], and wind power generation in China [36]. The aforementioned studies show that prediction accuracy of the seasonal GM(1,1) (SGM(1,1)) is higher than that of GM(1,1).

Seasonal fluctuations are included in fractional grey models. Wu et al. [37] used the seasonal fractional grey model (SFGM(1,1)) to forecast the air quality indicators in Xingtai and Handan in northern China. The results showed that SFGM(1,1) yielded higher prediction results than SGM(1,1) and GM(1,1). Zhang and Wu [38] used the particle swarm optimisation grey seasonal model with fractional order accumulation (PSO-FGSM(1,1)) to forecast power generation in China. Li et al. [39] used a novel grey seasonal model with fractional order accumulation to forecast monthly production of natural gas in China. Zhou et al. [40] used a seasonal fractional grey model to forecast air quality indicators in the Yangtze River Delta in China.

Data grouping-based grey modelling (DGGM) is a seasonal grey prediction method first proposed by Wang et al. [41] that has been used to forecast quarterly hydropower production data in China. Chen et al. [42] used DGGM(1,1) to forecast electric power consumption and electricity usage efficiency of industrial sectors in Zhejiang Province, China. Both studies showed that DGGM(1,1) yields higher prediction performance than GM(1,1). DGGM(1,1) was first combined with fractional order accumulation by Shou et al. [43] to create FDGGM(1,1), which had a significantly better prediction ability than DGGM(1,1) for monthly coal consumption in Liaoning Province, China. To the authors’ best knowledge, this is the only study of its kind in the literature. Therefore, FDGGM(1,1) should be used in more scientific fields.

Machine learning (ML) has recently been widely used in energy forecasting. ML techniques offer strong generalisation capability, the ability to process small samples, robustness, and the ability to cope with nonlinear systems. However, ML techniques are time-consuming, have weak interpretability, require large amounts of data for training [44], and over-fit some regression problems [45]. The use of ML techniques has become popular owing to their statistical accuracy and applicability.
to nonlinear models [46]. Khan et al. [47] presented a hybrid energy forecasting model based on ML techniques and used the extreme gradient boosting, categorical boosting, and random forest (RF) ML algorithms. Kaytez [48] forecasted net electricity consumption using the autoregressive integrated moving average (ARIMA) and least-square support vector machines (LS-SVM). Jawad et al. [49] presented a ML-based cost-effective electricity load forecasting model. Luis et al. [50] forecasted energy with ensemble ML methods. Titus et al. [51] predicted electricity demand and renewable energy generation using various ML algorithms. Soyliali [52] used ML approaches for short-/long-term electricity load forecasting. Carrera and Kim [53] employed ML techniques for photovoltaic prediction. Zhou et al. [54] presented an ML-based study of the on-site renewable electrical performance. Bedi and Toshniwal [55] proposed a deep learning framework to forecast electricity demand. Keles et al. [56] forecasted electricity spot prices using artificial neural networks (ANN). Zhao et al. [57] proposed a wind power prediction forecasting model based on extreme ML. Wang et al. [58] compared day-ahead photovoltaic power forecasting models based on deep learning neural network. Li et al. [59] proposed a hybrid deep learning model for short-term PV power forecasting. Theocharides et al. [60] forecasted day-ahead photovoltaic power production using ML and statistical post-processing.

So far, several grey prediction models and ML methods used in national energy sector forecasting have been summarised. ML models are preferred in part because they provide direct information about the results by generalising internal factors (e.g., gross domestic product, population, capacity factor of power plants, and losses due to maintenance and repair in power plants, etc.). However, ML models cannot answer the question of how much each factor affects the result or which factor is the most effective. Energy sector forecasts obtain values such as the total electricity generation of a country; however, internal factors affecting the results cannot be simultaneously published. This is especially true for data (e.g., national populations) that are not measured monthly. In these limited data conditions, grey prediction models and ML methods help researchers obtain results such as the electricity generation of a country.

Europe plays an important role in global electricity generation. In 2018, total electricity generation in Europe reached 4.17 TWh, which corresponds to 15.6% of the global total [61]. Additionally, renewable electricity generation in Europe accounts for approximately 20% of the global total [62]. In this study, the countries in Europe that generated the highest total electricity in 2019, France, Germany, Spain, Turkey, and the United Kingdom (UK), were selected. Total electricity generation in these countries constituted 51.2% of European electricity generation in 2019 [63]. The above-mentioned literature summaries reveal that research on the impact of the Covid-19 pandemic on European electricity generation is quite limited. This study aims to fill the gap in the literature by investigating the effect of the Covid-19 pandemic on electricity generation from renewables and non-renewables in the above-mentioned countries and by forecasting how the pandemic will reshape future electricity generation.

This study proposes a genetic algorithm (GA)-based seasonal fractional nonlinear grey Bernoulli model (SFANGBM(1,1)) that, to the best of the author’s knowledge, is the first in the literature. SFANGBM(1,1) combines FANGBM(1,1), which presents highly accurate annual data predictions and the seasonal fluctuation technique that enables monthly predictions, and a GA to obtain optimal parameters. Using FANGBM(1,1) can only present a disadvantage, especially in the estimation of monthly electricity generation where significant differences depend on seasonal conditions. SFANGBM(1,1) can be used to predict seasonal (e.g., monthly or quarterly) data and to estimate annual data by equating the value of the seasonal fluctuation index \( f_i \) to 1. Additionally, the proposed model is different from that of Jiang et al. [64] and based on a GA.

The above-mentioned studies reveal several gaps in the literature. This study differs from previous studies, and contributes the following:

1. Careful review of the above-mentioned literature reveals that the researchers focus on the current effects of the pandemic on the energy sector. However, studies forecasting the effects of the Covid-19 pandemic on the future of the energy sector in Europe have not been conducted. Therefore, this paper aims to answer the question of how European countries will reshape their energy sectors.

2. The seasonal fluctuation method has not yet been used with FANGBM(1,1) with GA technique. The SFANGBM(1,1) proposed in this study combines the seasonal fluctuation technique with FANGBM(1,1). In addition, a GA approach is used to obtain optimal parameters and to more accurately perform monthly electricity generation forecasting.

3. Fractional grey prediction models are a popular topic; however, only one study by Shou et al. [43] uses the afore-mentioned type of model to predict monthly coal consumption. The model deserves to be discussed widely in other scientific fields, and this pioneering study contributes to the literature using FDGGM(1,1).

4. To the best of the author’s knowledge, this is the first study that uses seasonal fractional grey prediction model and ML methods with the same dataset to forecast and compare performances. The accuracy of the proposed model was compared with basic ML methods, and the objective of achieving successful basic ML was reached.

5. Additionally, no current study in the literature measures the effects of Covid-19 on electricity generation in Europe using ML time series methods.

6. Electricity generation from total renewables and non-renewables in European countries has not yet been forecasted and compared since the start of the Covid-19 lockdown. This study fills this gap in the literature.

The rest of this paper is organised as follows. Section 2 provides the methodology of SFANGBM(1,1), FDGGM(1,1), and machine learning methods. Section 3 provides the results of the study performed in this paper. Section 4 presents the discussion of the results and makes comparisons with the literature. Finally, Section 5 presents the conclusions.

2. Methodology

This section presents the methodology of the GA based-SFANGBM (1,1), FDGGM(1,1), and machine learning methods. The seasonal fluctuation method has not yet been used with SFANGBM(1,1) reduces to SNGBM(1,1) and SGM(1,1). Finally, this section specifies which metric is used for performance evaluation.

2.1. Genetic algorithm based-seasonal fractional nonlinear grey Bernoulli model

The principle of seasonal fractional order accumulation is based on the \( r_N \) accumulated generation operation (r-SAGO), which is the combination of the seasonal fluctuation and GA-based fractional nonlinear grey Bernoulli model (FANGBM(1,1)). The following equations provide the GA-based SFANGBM(1,1) methodology:

The original non-negative sequence \( X^{(0)} \) is indicated as:

\[
X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n), n \geq 4 \}
\]

(1)

The seasonal fluctuation index \( f_i \), a dimensionless parameter, is calculated as [35]:

\[
 f_i = \frac{X_{\text{avg}}^{(0)}(i)}{X^{(0)}(i)}
\]

(2)

where \( M \) and \( N \) indicate the number of seasonal cycles in a year and the year of the \( i_{th} \) time point, respectively. In this study, \( X_{\text{avg}}^{(0)}(i) \) represents the average value for the monthly electricity generation at the \( i_{th} \) time
point, and $\sum_{n=0}^{(i)}(i)$ indicates the total average value of electricity generation for all seasons or months.

Using $f_{(i)}$, a seasonally affected original series can be created as:

$$X_{(i)}^{(0)} = \frac{X_{(i)}^{(1)}}{f_{(i)}} = X_{(i)}^{(0)}S = \left\{ X_{(i)}^{(0)}(1), X_{(i)}^{(0)}(2), X_{(i)}^{(0)}(3), \ldots, X_{(i)}^{(0)}(n) \right\}$$

(3)

$X_{(i)}^{(0)}S$ transforms to the $X_{(i)}^{(r)}$ as:

$$X_{(i)}^{(r)} = \left\{ X_{(i)}^{(0)}(1), X_{(i)}^{(0)}(2), X_{(i)}^{(0)}(3), \ldots, X_{(i)}^{(0)}(n) \right\}$$

(4)

where $X_{(i)}^{(r)}$ is the $r$th seasonal accumulated generating operation (r-SAGO) sequence of $X_{(i)}^{(0)}$, and $r$ denotes the fractional order value $r > 0$. $X_{(i)}^{(r)}$ can be formulated as:

$$X_{(i)}^{(r)}(k) = \sum_{i=1}^{k} X_{(i)}^{(r-1)}(i) = \sum_{i=1}^{k} \left( k - j + r - 1 \right) X_{(i)}^{(0)}S(i)$$

(5)

and

$$X_{(i)}^{(r)}(k) = \frac{(r + k - i - 1)(r + k - i - 2) \cdots (r + k - i - 3) \cdots (r + 1)}{(k - i)!}$$

(6)

When $r = 1$, $X_{(i)}^{(1)}(k)$ reduces to $X_{(i)}^{(1)}(k) = \sum_{i} X_{(i)}^{(0)}S(i)$, which indicates the first-order seasonal accumulated generating operation (1-SAGO) sequence of $X_{(i)}^{(0)}S$.

The whitening equation of the SFANGBM(1,1) can be given as:

$$\frac{dX_{(i)}^{(0)}(k)}{dt} + aX_{(i)}^{(0)}(k) = b\left(X_{(i)}^{(0)}(k)\right)^{\gamma}$$

(7)

and the discrete form can be written as:

$$X_{(i)}^{(r)}(k) - X_{(i)}^{(r)}(k - 1) + aX_{(i)}^{(0)}(k) = b\left(z_{(i)}^{(r)}(k)\right)^{\gamma}$$

(8)

where $\gamma$ indicates the power index value [25].

When $r = 1$, the whitening equation reduced to:

$$\frac{dX_{(i)}^{(1)}(k)}{dt} + aX_{(i)}^{(1)}(k) = b\left(X_{(i)}^{(1)}(k)\right)^{\gamma}$$

(9)

Wang et al. [34].

In Eq. (8), the form of $z_{(i)}^{(r)}(k)$ can be given as:

$$z_{(i)}^{(r)}(k) = 0.5X_{(i)}^{(r)}(k) + 0.5X_{(i)}^{(r)}(k - 1), k = 2, 3, \ldots, n$$

(13)

After valuing the power index value ($\gamma$) and fractional order value ($r$), parameters $a$, and $b$ of the whitening equation of the seasonal grey prediction models can be calculated using the least squares method as:

$$\begin{bmatrix}
\alpha_1 \\
\beta_1
\end{bmatrix} = \left[ B_{\gamma}^{T}B_{\gamma} \right]^{-1}B_{\gamma}^{T}Y_{\gamma}$$

(14)

where

$$B_{\gamma} = \begin{bmatrix}
-z_{(i)}^{(r)}(2) & \left( z_{(i)}^{(r)}(2) \right)^{\gamma} \\
-z_{(i)}^{(r)}(3) & \left( z_{(i)}^{(r)}(3) \right)^{\gamma} \\
\vdots & \vdots \\
-z_{(i)}^{(r)}(n) & \left( z_{(i)}^{(r)}(n) \right)^{\gamma}
\end{bmatrix}$$

$$Y_{\gamma} = \begin{bmatrix}
X_{(i)}^{(r)}(2) - X_{(i)}^{(r)}(1) \\
X_{(i)}^{(r)}(3) - X_{(i)}^{(r)}(2) \\
\vdots \\
X_{(i)}^{(r)}(n) - X_{(i)}^{(r)}(n - 1)
\end{bmatrix}$$

(15)

The predicted seasonal fractional accumulated values can be calculated by the following equation:

$$\begin{cases}
\hat{X}_{(i)}^{(r)}(1) = X_{(i)}^{(r)}(1) \\
\hat{X}_{(i)}^{(r)}(k) = \left[ \left( X_{(i)}^{(r)}(1) \right)^{1-\gamma} \frac{b_2}{a_2} + \frac{b_1}{a_1} \right]^{1/\gamma}
\end{cases}$$

(16)

In Eq. (16), $\hat{X}_{(i)}^{(r)}(k)$ can be converted to $\hat{X}_{(i)}(k)$ using the inverse accumulated generating operation matrix $A^{-\gamma}$, which is given as:

$$A^{-\gamma} = \begin{pmatrix}
1 & 0 & \cdots & 0 \\
0 & 1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1 \\
\end{pmatrix}$$

(17)

and the discrete form can be written as:

$$X_{(i)}^{(r)}(k) - X_{(i)}^{(r)}(k - 1) + a\hat{X}_{(i)}^{(r)}(k) = b\left(z_{(i)}^{(r)}(k)\right)^{\gamma}$$

(10)

This model is reduced to the season nonlinear grey Bernoulli model (SNGBM(1,1)), which is a combination of the NGBM(1,1) first proposed by Chen [65] and seasonal fluctuation.

When $\gamma = 0$ and $r = 1$; Eq. (9) and Eq. (10) reduce to the following equations, respectively:

$$\frac{dX_{(i)}^{(1)}(k)}{dt} + aX_{(i)}^{(1)}(k) = b$$

(11)

$$X_{(i)}^{(1)}(k) - X_{(i)}^{(1)}(k - 1) + a\hat{X}_{(i)}^{(1)}(k) = b$$

(12)

This model corresponds to SGM(1,1) or SFGM(1,1) first proposed by
2.2. Fractional data grouping-based grey modelling

This method differs from the time series analysis in previous models and predicts data on the basis of dimensionality reduction. After grouping the data, the fractional data grouping-based grey modelling (FDGGM(1,1)) realises the cross-period prediction. The FDGGM(1,1) methodology is implemented according to the following formula [43]:

Step 1: The data sequences of consecutive months in consecutive years are, respectively:
\[
X^{(0)}(i) = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(i), \ldots, x^{(0)}(n)\}
\]
\[
X^{(r)}(i) = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(i), \ldots, x^{(r)}(n)\}
\]
\[
X^{(n)}(i) = \{x^{(n)}(1), x^{(n)}(2), \ldots, x^{(n)}(i), \ldots, x^{(n)}(n)\}
\]
(20)

where \(n\) is the number of consecutive months, and \(m\) is the number of consecutive years.

Step 2: The continuous time series in the unit of months is grouped into the continuous time series in the unit of years, and the new series is:
\[
X^{(0)}(1) = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}
\]
\[
X^{(r)}(i) = \{x^{(r)}(i), x^{(r)}(i+1), \ldots, x^{(r)}(n)\}
\]
\[
X^{(n)}(i) = \{x^{(n)}(i), x^{(n)}(i+1), \ldots, x^{(n)}(n)\}
\]
(21)

Step 3: By the following formula:
\[
x^{(r)}(i) = \sum_{j=1}^{k} C^{r}_{k,j} y^{(0)}(i)
\]
(22)

Fractional order accumulation was performed for each new sequence, and the order accumulation sequence was obtained as:
\[
X^{(r)}(i) = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)\}
\]
(23)

In Eq. (22), \(C^{0}_{k,1} = 1, C^{r}_{k,k} = 0\),
\[
C^{r}_{k,j} = \frac{(k-j+1)(k-j+2)\cdots(r+1)r}{(k-j)^r}
\]
(24)

Step 4: The background value of the \(r\) order accumulation sequence \(X^{(r)}(i)\) is generated and calculated:
\[
B = \begin{bmatrix}
-\frac{x_i^{(r)}(i)}{x_i^{(r)}(i)} \\
\vdots \\
-\frac{x_n^{(r)}(i)}{x_i^{(r)}(i)}
\end{bmatrix}, \quad Y = \begin{bmatrix}
x^{(r)}(i) - x^{(r)}(i) \\
\vdots \\
x^{(n)}(i) - x^{(n)}(i)
\end{bmatrix}
\]
(25)

where \(x_i^{(r)}(i) = \frac{\sum_{j=1}^{n} r x^{(r)}(j)}{2} \) is the direct average generation sequence of \(X^{(r)}(i)\).

Step 5: As the least square estimation minimises the error sum of squares, the least square estimation is used to obtain the parameters; the unknown parameters can be solved by the following formula:
\[
\begin{bmatrix}
a \\
b
\end{bmatrix} = (B^T B)^{-1} B^T Y
\]
(26)

Step 6: Plugging \(a\) and \(b\) into the time response function:
\[
\hat{x}_{k+1}^{(r)}(i) = \left(\begin{array}{c}
x_1^{(r)}(i) \\
\vdots \\
x_n^{(r)}(i)
\end{array}\right) + \frac{b}{a}
\]
(27)

where \(\hat{x}_{k+1}^{(r)}(i)\) is the fitting value, when \(j = k + 1\). The prediction sequence is obtained:
\[
\hat{X}_{k}^{(r)}(i) = \left\{\hat{x}_{1}^{(r)}(i), \hat{x}_{2}^{(r)}(i), \ldots, \hat{x}_{n}^{(r)}(i), \ldots\right\}
\]
(28)

Step 7: The \(r\) order subtraction of sequence \(\hat{X}_{k}^{(r)}(i) = (\hat{x}_{1}^{(r)}(i), \hat{x}_{2}^{(r)}(i), \ldots, \hat{x}_{m}^{(r)}(i), \ldots)\) is completed and the sequence is obtained as:
\[
\hat{x}^{(r)}(i) = \hat{x}_{1}^{(r)}(i) - \hat{x}_{k}^{(r)}(i)
\]
(29)

where
\[
ad^{(r)}\hat{x}^{(r)}(i) = \hat{x}_{1}^{(r)}(i) - \hat{x}_{k}^{(r)}(i)
\]
(30)

Step 8: The predicted value after reduction is:
\[
\tilde{X}^{(0)}(i) = \left\{\tilde{x}_{1}^{(0)}(i), \tilde{x}_{2}^{(0)}(i), \ldots, \tilde{x}_{n}^{(0)}(i), \ldots\right\}
\]
(31)

The prediction sequence is reduced to the original time series dimension, and the prediction sequence of the original data is:
\[
\tilde{X}_{1}^{(0)} = \left\{\tilde{x}_{1}^{(0)}(1), \tilde{x}_{1}^{(0)}(2), \ldots, \tilde{x}_{1}^{(0)}(i), \tilde{x}_{1}^{(0)}(n)\right\}
\]
\[
\tilde{X}_{n}^{(0)} = \left\{\tilde{x}_{n}^{(0)}(1), \tilde{x}_{n}^{(0)}(2), \ldots, \tilde{x}_{n}^{(0)}(i), \tilde{x}_{n}^{(0)}(n)\right\}
\]
\[
\tilde{X}_{m+1}^{(0)} = \left\{\tilde{x}_{m+1}^{(0)}(1), \tilde{x}_{m+1}^{(0)}(2), \ldots, \tilde{x}_{m+1}^{(0)}(i), \tilde{x}_{m+1}^{(0)}(n)\right\}
\]
\[
\tilde{X}_{m+2}^{(0)} = \left\{\tilde{x}_{m+2}^{(0)}(1), \tilde{x}_{m+2}^{(0)}(2), \ldots, \tilde{x}_{m+2}^{(0)}(i), \tilde{x}_{m+2}^{(0)}(n)\right\}
\]
\[
\vdots
\]
(32)

2.3. Machine learning methods

In time series analysis (unlike in other classical methods), ML evaluates multivariate data rather than considering the data as a single variable. Therefore, the time parameter is divided into small and definite periods to determine statistical properties and their product. The new variables allow the use of multivariate time series analysis and the discovery of hidden patterns over time [66]. In this study, linear regression, support vector machines, and RF algorithms were employed to forecast the monthly electricity generation of European countries. The algorithms are explained in the following sub-sections.

2.3.1. Linear regression

Linear regression is the most essential and basic methodology employed to discover connections between factors described by numerical data. In this methodology, the information pattern is found, and forecasting is performed appropriately. All free factors should be specified [67]. Multi-variable linear regression is expressed as following formula:
\[
f(x, y, z) = w_1 x + w_2 y + w_3 z
\]
(33)
where \( w \) represents the coefficients; and \( x, y, z \) represent the attributes.

### 2.3.2. Support vector machines

Support vector machines (SVM) is a supervised ML algorithm also used as a regression method. Support vector regression uses the same classification concepts as SVM and employs kernel functions to perform more accurate linear separation by transforming the data into a higher dimensional feature space [68]. The polynomial kernel is the most common and is defined by the following formula:

\[
k(x_i, x_j) = (x_i \cdot x_j)^d
\]

where \( d \) is the degree of the kernel.

### 2.3.3. Random forest

RF is an ensemble machine learning algorithm used for regression and classification [69] that comprises multiple collectively run decision trees. Each tree finds a prediction, which is subjected to a vote. Then the prediction with the most votes is selected as the model prediction [70].

### 2.4. Model accuracy analysis

In this study, parameters \( \gamma \) and \( r \) of the grey prediction models are obtained by using a GA technique. Calculation of the absolute percentage error (APE)—which denotes the accuracy between the predicted and original values—are used to obtain the optimal \( \gamma \) and \( r \) parameters. Additionally, to measure the accuracy performance of the prediction models, the mean absolute percentage error (MAPE) and root mean square error (RMSE) values are used in this study. The prediction model classifies MAPE lower than 10% as an excellent level; the range of 10–20% is a good level. The calculation of APE, MAPE, and RMSE can be expressed by the following equations [39]:

\[
APE(\%) = \frac{\left| u(i) - \hat{u}(i) \right|}{u(i)} \times 100
\]

\[
MAPE(\%) = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{u(i) - \hat{u}(i)}{u(i)} \right| \times 100
\]

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

where \( u, \hat{u}, \) and \( u \) denote the original data, the predicted data, and the average of the original data, respectively. The goodness of fit values of the prediction models can be formulated as [71]:

\[
Goodness \ of \ fit \ (\%) = 100 - APE(\%)
\]

Fig. 1 presents the key steps of the prediction models in this study in a flowchart scheme.

### 3. Results

This section presents obtained data, accuracy performance results of the grey prediction and machine learning models, and forecasting results of monthly and quarterly electricity generation from renewables and non-renewables in the selected countries.

#### 3.1. Data description and model parameters

This study evaluated monthly electricity generation data from renewables and non-renewables for prediction and forecasting. Non-renewables indicate the sum of combustible fuels, natural gas, oil and petroleum products, nuclear fuels, and other fuels. Renewables denote the sum of hydro, geothermal, wind, solar, and other renewable energies. The statistical data of electricity generation from renewables and non-renewables in the selected countries are provided in Table 1.

![Flowchart scheme](image-url)
non-renewables are taken from Eurostat [63]. Additionally, nuclear power generation in Turkey has not yet entered operation, and Spain and the UK have no geothermal power plants. Therefore, total renewable and non-renewable sources are evaluated in this study. Moreover, the data focuses on France, Germany, Spain, Turkey, and the UK, which had the highest total electricity generation values at the end of 2019. Fig. 2 shows the monthly electricity generation from renewables and non-renewables for France, Germany, Spain, Turkey, and the UK from January 2017 to September 2020. France and Germany have the highest electricity generation from non-renewables and renewables, respectively.

Before establishing the grey prediction models, the seasonal fluctuation ($f_i$) values of the data to be used for forecasting are calculated by Eq. (2). The mean electricity generation for the same month from renewables and non-renewables for France, Germany, Spain, Turkey, and the UK in different years are obtained. Table 1 provides the seasonal fluctuation values of the selected countries. The seasonal fluctuation index represents the monthly electricity generation average of a region over the past few years. Index values greater than and lesser than 1 denote levels of electricity generation higher and lower than the annual average, respectively. The selected countries are all located in the middle and high latitudes of the Northern Hemisphere; thus, electricity production is high in November, December, and January and slows significantly from April to June.
3.2. Model prediction accuracy

Monthly electricity generation from renewables and non-renewables is predicted with four seasonal grey prediction models and three ML methods for the selected countries using the data in Fig. 2. Fig. 3a and b provide the APE values of the prediction models for monthly electricity generation from non-renewables and renewables in the selected countries, respectively. Fig. 3 shows that the APE value largely depends on the regularity of the original data. In this study (unlike with grey prediction models), ML methods use approximately 50% of the data for training. Therefore, the results of APE values in ML methods are shown since December 2018. Fig. 3 shows the detailed accuracy of the estimates for the countries. The APE values reveal that the GA-based SFANGBM(1,1), SNGBM(1,1), and SGM(1,1) methods yield similar results. Although the accuracy of the prediction decreases due to variability during seasonal transitions for all methods, the SVM method (a ML method) has the lowest APE values. APE values of SVM before and after Covid-19 are not significantly different. However, in other methods, the APE values increase in periods when the Covid-19 effect is felt.

Table 2 gives the MAPE and RMSE values of the evaluated models for the prediction of electricity generation from renewables and non-renewables in the selected countries. ML methods generally give better results than other methods. More specifically, the SVM method has better MAPE and RMSE values than other methods. The FDGGM(1,1) method is only better than SVM for electricity generation from renewables in Spain; compared to other countries, the closest results to SVM are obtained with the FDGGM(1,1) method. SFANGBM(1,1) yields higher prediction performance than SNGBM(1,1) and SGM(1,1) in all cases. Moreover, seasonal fluctuation techniques improve the accuracy results of the grey prediction models in all cases. GA-based SFANGBM(1,1), SNGBM(1,1), and SGM(1,1) yield higher prediction results than FANGBM(1,1), NGBM(1,1), and GM(1,1), respectively. Therefore, the principal advantage of SFANGBM(1,1) is prediction performance better than that of FANGBM(1,1) for monthly electricity generation. Thus, ML yields better results due to training with more data than the other methods. Therefore, ML methods learn data behaviour better. Additionally, SVM fits nonlinear data well and provides a powerful prediction model.

3.3. Forecasting results of the prediction models

Fig. 5 presents the comparison of predicted and forecasted results of monthly electricity generation from renewables and non-renewables in France, Germany, Spain, Turkey, and the UK using the SFANGBM(1,1), SNGBM(1,1), SGM(1,1), FDGGM(1,1), SVM, linear regression, and RF models. All grey models predicted and forecasted monthly electricity generation in the selected countries from January 2017 to September 2020 and from October 2020 to December 2021, respectively. Unlike the grey prediction models, ML methods predicted the actual values from December 2018 to September 2020. Fig. 5a and b show the start of the Covid-19 lockdown on March 2020. Fig. 5 presents the comparison of predicted and forecasted results of monthly electricity generation from renewables and non-renewables in France, Germany, Spain, Turkey, and the UK using the SFANGBM(1,1), SNGBM(1,1), SGM(1,1), FDGGM(1,1), SVM, linear regression, and RF models. All grey models predicted and forecasted monthly electricity generation in the selected countries from January 2017 to September 2020 and from October 2020 to December 2021, respectively. Unlike the grey prediction models, ML methods predicted the actual values from December 2018 to September 2020. Fig. 5a and b show the start of the Covid-19 lockdown on March 2020.

Table 2 reveals that SFANGBM(1,1) and SVM have the lowest MAPE value among the seasonal grey prediction models and ML methods, respectively. Fig. 6 presents the prediction and forecasting results of electricity generation from renewables and non-renewables for France using the SFANGBM(1,1), SVM, and FDGGM(1,1) models, which are based on a data grouping method. France has the highest electricity generation from non-renewables (Fig. 2a). Fig. 6 presents the prediction and forecasting results of electricity generation from renewables and non-renewables for France in the four quarter period using the above-mentioned prediction models. Analysis of the four quarters shows that the prediction models forecast that the upward trend in electricity generation from renewables will continue. In addition, the most significant effect of Covid-19 on electricity generation from non-renewables was the sharp decrease in the 2nd and 3rd quarters. Figs. 7-11 present the actual and forecasted results of quarterly electricity generation from non-renewables and renewables and the share of renewables in total electricity generation for France, Germany, Spain, Turkey, and the UK. Q1, Q2, Q3, and Q4 cover the three-month periods from January–March, April–June, July–September, and October–December, respectively. Additionally, Q1, Q2, and Q3 are only forecasted for 2021; whereas Q4 is forecasted for 2020 and 2021.

### Table 1

| Month       | France | Germany | Spain | Turkey | UK  |
|-------------|--------|---------|-------|--------|-----|
| January     | 1.3361 | 1.2314  | 1.1234| 1.0977 | 1.2211|
| February    | 1.1736 | 1.0701  | 0.9632| 0.9672 | 1.0457|
| March       | 1.1225 | 1.0447  | 0.8537| 0.8789 | 1.0667|
| April       | 0.9336 | 0.8765  | 0.7929| 0.7170 | 0.9437|
| May         | 0.9009 | 0.8624  | 0.8411| 0.7419 | 0.9221|
| June        | 0.8249 | 0.8720  | 0.9645| 0.8914 | 0.8931|
| July        | 0.8861 | 0.9506  | 1.1584| 1.2050 | 0.9702|
| August      | 0.8476 | 0.9906  | 1.1435| 1.1547 | 0.9021|
| September   | 0.8729 | 0.9897  | 1.0826| 1.1437 | 0.9108|
| October     | 0.9420 | 1.0087  | 1.0949| 1.0922 | 0.9860|
| November    | 1.0347 | 1.1355  | 1.0249| 1.0920 | 1.1053|
| December    | 1.1589 | 1.0051  | 0.9825| 1.0857 | 1.0747|
| January     | 1.1093 | 1.0245  | 1.0854| 0.9593 | 1.1422|
| February    | 1.1231 | 1.0188  | 0.9965| 0.9147 | 1.0607|
| March       | 1.2777 | 1.1690  | 1.2740| 1.1313 | 1.1027|
| April       | 0.9674 | 1.0430  | 1.0687| 1.1871 | 0.9372|
| May         | 1.1157 | 0.9860  | 1.0343| 1.2352 | 0.8964|
| June        | 1.0582 | 0.9548  | 0.9381| 1.0399 | 0.8711|
| July        | 0.8793 | 0.9148  | 0.9362| 1.0628 | 0.8495|
| August      | 0.7680 | 0.8856  | 0.8639| 1.0883 | 0.9133|
| September   | 0.7114 | 0.8840  | 0.8125| 0.8371 | 0.9703|
| October     | 0.7818 | 1.0880  | 0.8034| 0.6733 | 1.0953|
| November    | 0.9636 | 0.8877  | 1.0359| 0.7031 | 1.0743|
| December    | 1.2410 | 1.1835  | 1.1477| 1.0160 | 1.1804|
Fig. 3. APE values of electricity generation from (a) renewables and (b) non-renewables in France, Germany, Spain, Turkey, and the UK.
Table 2: MAPE and RMSE values of prediction models for this study.

| Country   | Prediction model | Electricity generation from non-renewables | Electricity generation from renewables |
|-----------|------------------|--------------------------------------------|----------------------------------------|
|           | MAPE(%) RMSE      | MAPE(%) RMSE                              |
| France    | GM(1,1)           | 13.453 5478 19.805 1984                   |
|           | NGBM(1,1)         | 13.187 5332 19.784 1983                   |
|           | FANGBM(1,1)       | 12.174 5203 18.403 2113                   |
|           | SGM(1,1)          | 5.092 2015 8.526 1008                     |
|           | SNGBM(1,1)        | 3.843 1614 8.156 1005                     |
|           | SFANGBM(1,1)      | 3.718 1617 7.772 1058                     |
|           | FDGGM(1,1)        | 1.916 1043 0.787 151                      |
|           | Linear regression | 3.406 1727 7.438 784                     |
|           | SVM               | 0.084 63 0.971 456                       |
|           | RF                | 2.085 1003 4.314 516                     |
| Germany   | GM(1,1)           | 11.011 3584 11.113 2480                   |
|           | NGBM(1,1)         | 10.446 3436 11.054 2470                   |
|           | FANGBM(1,1)       | 10.107 3302 10.618 2628                   |
|           | SGM(1,1)          | 7.413 2431 6.898 1730                     |
|           | SNGBM(1,1)        | 6.670 2251 6.524 1714                     |
|           | SFANGBM(1,1)      | 6.663 2251 6.344 1731                     |
|           | FDGGM(1,1)        | 1.777 1093 1.482 604                     |
|           | Linear regression | 7.986 2355 7.125 1907                    |
|           | SVM               | 1.090 908 0.407 476                      |
|           | RF                | 3.412 1153 3.838 1067                    |
| Spain     | GM(1,1)           | 13.719 1961 13.811 1527                   |
|           | NGBM(1,1)         | 12.190 1910 13.439 1526                   |
|           | FANGBM(1,1)       | 12.914 1907 12.866 1610                   |
|           | SGM(1,1)          | 7.092 1077 8.444 1021                     |
|           | SNGBM(1,1)        | 6.842 1062 8.428 1038                     |
|           | SFANGBM(1,1)      | 6.737 1056 7.894 1091                     |
|           | FDGGM(1,1)        | 2.966 699 0.592 94                       |
|           | Linear regression | 6.696 976 12.621 1286                    |
|           | SVM               | 0.619 315 0.662 281                      |
|           | RF                | 3.558 581 3.713 423                      |
| Turkey    | GM(1,1)           | 18.640 2816 19.914 1919                   |
|           | NGBM(1,1)         | 17.748 2755 19.903 1920                   |
|           | FANGBM(1,1)       | 17.747 2756 19.553 1905                   |
|           | SGM(1,1)          | 7.898 1336 10.102 1144                   |
|           | SNGBM(1,1)        | 7.839 1337 10.099 1146                   |
|           | SFANGBM(1,1)      | 7.838 1331 8.319 981                     |
|           | FDGGM(1,1)        | 0.432 106 5.176 893                      |
|           | Linear regression | 7.104 1086 10.229 1253                   |
|           | SVM               | 0.034 5 1.354 409                       |
|           | RF                | 4.358 721 4.185 520                      |
| UK        | GM(1,1)           | 9.733 1984 10.605 1335                   |
|           | NGBM(1,1)         | 9.695 1942 10.492 1338                   |
|           | FANGBM(1,1)       | 9.421 1869 9.506 1334                   |
|           | SGM(1,1)          | 6.544 1224 6.078 818                     |
|           | SNGBM(1,1)        | 6.095 1155 6.065 822                     |
|           | SFANGBM(1,1)      | 6.093 1154 6.060 820                     |
|           | FDGGM(1,1)        | 1.399 535 1.229 245                      |
|           | Linear regression | 5.301 1026 3.257 454                    |
|           | SVM               | 1.656 859 0.019 2                       |
|           | RF                | 3.300 695 3.310 425                      |

Fig. 7a presents the actual and forecasted results of quarterly electricity generation from non-renewables in France. Electricity generation from non-renewables is estimated to decrease in Q1 of 2021 compared to the same period in 2017–2020. Except for SGM(1,1) and RF, other prediction models estimate that non-renewable electricity generation will decrease in Q2 and Q3 of 2021. Electricity generation from non-renewables is predicted to decrease in Q4 of 2021 compared to Q4 of 2020. All grey prediction models forecast that electricity generation from non-renewables will decrease in Q4 of 2021 compared to the Q4 of previous years. All grey prediction models and SVM (Fig. 7c) indicate that the share of renewables in total electricity generation in France will increase in all periods compared to the same periods of the previous year.

Fig. 8a presents the actual and forecasted results of quarterly electricity generation from non-renewables in Germany. Electricity generation from non-renewables decreased in all quarterly periods compared to the same periods in previous years. Except for SGM(1,1) and SVM, the other prediction models forecast that electricity generation from non-renewables will decrease in Q1 of 2021 compared with Q1 of 2020. The prediction models show that electricity generation from non-renewables in Q1, Q2, and Q3 of 2021 will be below the 2017–2020 average. Except for SVM, other prediction models estimate that non-renewable electricity generation will decrease in Q4 of 2021 compared to the same period of previous years. Fig. 8b presents the forecasting results of quarterly electricity generation from renewables in Germany. Only the results of FDGGM(1,1) and SVM are compatible with the electricity generation, which continuously increased in Q1 from 2017 to 2020. All the prediction models forecast that electricity generation from renewables will increase in Q2 of 2021 compared to the same period of 2020. All the prediction models, except SVM, estimate that renewable electricity generation will increase in Q3 of 2021 compared to the same period of the previous years. All the grey prediction models give results close to the actual data of 2020.

Fig. 9a illustrates the actual and forecasted results of quarterly electricity generation from non-renewables in Spain. Electricity generation from non-renewables is forecast to decrease in Q1 of 2021 compared to the same period from 2017 to 2020. All the prediction models, except the linear regression model, forecast that non-renewable electricity generation will decrease in Q2 of 2021 compared to Q2 of 2020. Only the SVM model indicates that electricity generation from non-renewables will increase in Q3 of 2021 compared to Q3 of 2020. The results of all the prediction models show that electricity generation from non-renewables will increase in Q4 of 2020 and will decrease in 2021 compared to the same periods of the previous years. Fig. 9b gives the forecasting results of quarterly electricity generation from renewables in Spain. All grey prediction models and SVM estimate that renewable electricity generation will increase in Q1 of 2021 compared to Q1 of 2020. All the prediction models, except SVM and RF, indicate that renewable electricity generation will increase in Q2 of 2021 compared to Q2 of 2020. All the prediction models estimate that electricity generation from renewables in Q3 of 2021 will exceed the average of the same periods from 2017 to 2020.

Fig. 10a presents the actual and forecasted results of quarterly electricity generation from non-renewables in Turkey. All the prediction models, except FDGGM(1,1) and SVM, forecast that electricity generation from non-renewables will decrease in Q1 of 2021 compared to Q1 of 2020. The grey prediction models give results close to the actual data of the previous year, whereas the ML methods give higher results for electricity generation from non-renewables in Q2 of 2021. All the
Fig. 4. Goodness of fit values of the SFANGBM(1,1), SNGBM(1,1), and FANGBM(1,1) for the prediction of non-renewables (a) and renewables electricity generation (b) in the selected countries.
Fig. 5. Predicted and forecasted results of monthly electricity generation from (a) renewables and (b) non-renewables in France, Germany, Spain, Turkey, and the UK.
Fig. 6. Actual and forecasted results of monthly electricity generation in a quarterly period from (a) renewables and (b) non-renewables for France using selected prediction models.
prediction models, except FDGGM(1,1), estimate that non-renewables electricity generation will decrease in Q3 of 2021 compared to Q3 of 2020. The other prediction models (except for SVM) forecast that non-renewable electricity generation will decrease in Q4 of 2021 compared to the same period of previous years. SVM gives extremely high results for Q4 of 2020 and 2021. Fig. 10b illustrates the actual and forecasted results of quarterly electricity generation from renewables in Turkey. All the prediction models estimate that electricity generation from renewables in Q1, Q2, and Q3 of 2021 will exceed the average of the same periods from 2017–2020. Fig. 10c presents the actual and forecasted results of the quarterly share of renewables in total electricity generation in Turkey, which approximately ranges from 47% to 51% for Q1 in 2021, according to the prediction models. The SFANGBM(1,1) and RF models estimate that this share will decrease in Q2 of 2021 compared to Q2 of 2020. The other prediction models, except FDGGM(1,1), forecast that this share will increase in Q3 of 2021 compared to Q3 of 2020. Additionally, the grey prediction model results show that the share of renewables in total electricity generation will increase in Q4 of 2020 and
2021 compared to the same period in previous years. Fig. 11a presents the actual and forecasted results of quarterly electricity generation from non-renewables in the UK. All the prediction models, except SGM(1,1), forecast decreased electricity generation from non-renewables in Q1 of 2021 compared to Q1 of previous years. The actual annual Q2 and Q3 data show a decrease in electricity generation from 2017 to 2020. All prediction models forecast that electricity generation from non-renewables in Q2 and Q3 will be below the average of the same periods from 2017 to 2020. All the prediction models forecast that electricity generation from non-renewables will decrease in Q4 of 2020 and 2021 compared to the same period in previous years. Fig. 11b presents the actual and forecasted quarterly electricity generation from renewables in the UK. The actual values of electricity generation from renewables increased in Q1, Q2, and Q3 from 2017–2020. Fig. 11c gives the actual and forecasted results of the share of renewables in total electricity generation in the UK. The prediction models indicate that
The share of renewables in total electricity generation will exceed the average of the same periods in previous years. The grey prediction models forecast that the share of renewables in total electricity generation in Q1, Q2, and Q3 of 2021 will range from 47% to 58%, 48%–53%, and 44%–51%, respectively.

Fig. 12 presents the actual and forecasted results of annual electricity generation from renewables and non-renewables for the selected countries using the prediction models. The prediction models, except RF, show that electricity generation from renewables will increase by the end of 2021 in France. The prediction models, except SGM(1,1), indicate that electricity generation from non-renewables in France will decrease by the end of 2021. The prediction models, except SFANGBM(1,1) and RF, show that renewable electricity generation in Germany will increase by the end of 2021. The results of all the prediction models indicate that electricity generation from non-renewables in Germany will decrease by the end of 2021. The prediction models, except for SVM and RF, show that electricity generation from renewables will increase by the end of 2021 in Spain. Additionally, all prediction models show that electricity
generation from non-renewables in Spain will decrease by the end of 2021. Renewable electricity generation in Turkey in 2020 will not change significantly from 2019 levels. Only FDGGM(1,1) and SVM forecast that electricity generation from non-renewables will increase in 2020 and 2021 in Turkey; the other models forecast a decrease. The prediction models, except for RF, forecast that electricity generation from renewables will increase by the end of 2021 in the UK. Additionally, all prediction models forecast that electricity generation from non-renewables will decrease by the end of 2021 in the UK.

Fig. 13 presents the actual and forecasted annual share of renewables in total electricity generation for France, Germany, Spain, Turkey, and the UK. The forecasted values for 2020 are calculated as the sum of the forecasted value of Q4 using prediction models and actual values from Q1, Q2, and Q3. The year 2021 includes the sum of the forecasted values of Q1, Q2, Q3, and Q4 using the prediction models. The share of renewables in total electricity generation in France increased from 16.5%
in 2017 to 20.1% in 2019 and are forecast to reach 23.9%–26.7% and 25.0%–33.4% in 2020 and 2021, respectively. Additionally, all seven prediction models estimate an increased share compared to that of the previous years. The share of renewables in total electricity generation in Germany increased from 31.7% in 2017 to 38.9% in 2019 and is forecast to reach 44.3%–46.8% and 43.6%–53.5% for 2020 and 2021, respectively. Additionally, all the prediction models estimate an increased share from 2019 to 2021 ranging from 44.0% to 46.8% and 43.6%–53.5% for 2020 and 2021, respectively. Turkey has the highest share of annual electricity generation from renewables in total electricity generation in 2019 among the selected countries. The share of renewables increased continuously from 2017 to 2019 and is forecast to range from 40.3% to 46.4% in 2020 and 41.4%–53.0% in 2021. The share of renewables in total electricity generation in Spain decreased from 39.1% in 2018 to 38.2% in 2019, but all the prediction models show an increased share from 2019 to 2021 ranging from 44.0% to 46.8% and 43.6%–53.5% for 2020 and 2021, respectively. Turkey has the highest share of annual electricity generation from renewables in total electricity generation in 2019 among the selected countries. The share of renewables increased continuously from 2017 to 2019 and is forecast to range from 40.3% to 46.4% in 2020 and 41.4%–53.0% in 2021. The share of renewables in total electricity generation in the UK increased from 33.1% in 2017 to 39.0% in 2019 and is predicted.

Fig. 11. Actual and forecasted results of quarterly electricity generation from (a) non-renewables and (b) renewables and (c) share of renewables in total electricity generation for the UK using prediction models.
Fig. 12. Actual and forecasted results of annual electricity generation from (a) renewables and (b) non-renewables for the selected countries using prediction models.
Fig. 13. Actual and forecast results of the share of annual electricity generation from renewables in total electricity generation for the selected countries using prediction models.
to range from 44.8% to 47.3% and 45.1%–56.9% in 2020 and 2021, respectively.

4. Discussion

FANGBM(1,1) and its reduced forms (NGBM(1,1) and GM(1,1)) are commonly used for annual data forecasting. The accuracy performance of these models is typically low for the prediction of monthly data owing to significant changes. The results of this study justify this hypothesis. SFANGBM(1,1), SNGBM(1,1), and SGM(1,1) incorporate the seasonal fluctuation technique and show better prediction results than FANGBM (1,1), NGBM(1,1), and GM(1,1), respectively, in all cases. Therefore, the results of this study are consistent with those of previous studies [34,35], and [37].

The accuracy performance of the prediction models was evaluated. SFANGBM(1,1) produced more accurate prediction performance than SNGBM(1,1) and SGM(1,1) in all cases. This result is based on optimising the power index value ($\gamma$) and fractional order value ($r$) parameters in SFANGBM(1,1). Additionally, SNGBM(1,1) gives higher prediction results than SGM(1,1) in all cases due to the optimisation of $r$.

The performance accuracy of ML methods is also compatible with the results of previous studies [66] and [72]. Thus, SVM is better than other ML methods for time series prediction. SVM also largely outperforms other non-ML time series models. Furthermore, neither linear regression nor RF methods have higher accuracy or better MAPE values than FDGGM(1,1).

SVM and FDGGM(1,1) yield either extremely high or very unreasonable results compared to other models for the forecasting of monthly electricity generation from renewables for November–December 2021, in France, Germany, Turkey, and the UK and monthly electricity generation from non-renewables in November–December 2021, in Germany, Spain, and the UK (Fig. 5). SVM and FDGGM(1,1) present the highest accuracy in all cases. However, SFANGBM(1,1) yields more reliable forecasting results, with both MAPE values below 10% and lack of the excessive deviation found in SVM and FDGGM(1,1) in all the cases.

Electricity generation from total non-renewables in Q2 (April–June total) of 2020 when the first lockdown was applied decreased by 11%–25% compared to the previous year for the selected countries (Figs. 7–11). Fig. 14a depicts the reason for this decline after the lockdown. In France, nuclear energy—which constitutes the largest share of electricity generation from non-renewables—decreased by 21% in Q2 after the lockdown. In Germany, the highest decline in electricity generation from non-renewables (mainly coal) was 44%. In Spain, natural

![Comparison between electricity generation from non-renewable sources in (a) Q2 and (b) Q3 before and after lockdown.](image-url)
gas and nuclear energy—which have the largest share of electricity generation from non-renewables—decreased by 29% and 19%, respectively. In Turkey, electricity generation from coal and natural gas sources in Q2 decreased by 4% and 27%, respectively. In the UK, electricity generation from natural gas sources decreased dramatically in Q2. Fig. 14b presents the comparison between electricity generation from non-renewable sources in Q3 before and after the Covid-19 lockdown. In Q3 of 2020, during a softer Covid-19 lockdown than that in Q2, the decline in nuclear power generation occurred at the same rate as in Q2 for France. However, electricity generation from natural gas in Q3 increased significantly compared to Q2. Electricity generation from coal in Germany in the Q3 of 2020 has recovered compared to Q2 of the same year. In Spain, natural gas and nuclear power generation increased in Q3 of 2020 compared to Q2 of 2020. Electricity generation from natural gas increased significantly in Q3 of 2020 compared to Q2 of 2020 in Turkey and the UK. However, in the UK, the decline in nuclear electricity generation in Q2 increased further in Q3.

A sharp decline in nuclear power generation, especially in France, affected the total electricity generation from non-renewables after the implementation of the first Covid-19 lockdown. This result can be attributed to the closure of nuclear reactors and to scheduled maintenance [73]. Additionally, this study forecasted that the share of renewables in electricity generation for the selected countries will increase by the end of 2021. The Covid-19 pandemic might accelerate the progress towards national renewable energy targets.

5. Conclusions

The Covid-19 pandemic has caused changes in the energy sector of many countries. Thus, how the future of the energy sector will be reshaped is a matter of interest for decision-makers. This study aimed to project how much electricity generation from renewables and non-renewables will be produced in France, Germany, Spain, Turkey, and the UK by the end of 2021 by considering the effects of the Covid-19 pandemic on electricity generation. Four seasonal grey prediction models and three ML models were used as forecasting tools. The conclusions are as follows:

- The seasonal fluctuation technique increased the prediction performance of grey prediction models. The proposed model is a GA-based seasonal fractional nonlinear grey Bernoulli model (FDGGM(1,1)) that presents higher accuracy results than the fractional nonlinear grey Bernoulli model for all cases.
- The FDGGM(1,1) and support vector machine models present the highest prediction performance with the lowest MAPE values for all cases.
- In Q2 (April–June total) of 2020, electricity generation from non-renewables decreased compared to Q2 of previous years for all countries. Electricity generation from non-renewables in Q3 (July–September total) of 2020 decreased in France, Germany, Spain, and the UK compared to Q3 of 2019.
- Electricity generation from renewables in Q2 of 2020 increased in every country except Turkey compared to Q2 of 2019. In Q3 of 2020, electricity generation from renewables increased compared to Q3 of 2019 for all selected countries.
- The share of renewables in total electricity generation in Q2 and Q3 of 2020 increased in France, Germany, Spain, and the UK compared to the same period of 2019. In Turkey, this share decreased in Q3 of 2020 compared to Q3 of 2019.
- Turkey had the highest share of renewables in total electricity generation among the selected countries in 2019. Prediction model results indicate that the share will range from 40.3% to 46.4% in 2020 and 41.4%–53.0% in 2021.
- All grey prediction models and support vector machines forecast that the share of renewables in total electricity generation will increase continuously in France, Germany, Spain, and the UK by the end of 2021.
- This study aimed to propose a new grey model. Therefore, the accuracy of the proposed model was compared with that of basic ML methods. The basic ML threshold was successfully reached. More complex ML methods will be used as a benchmark in future studies.

This study has certain limitations.

- Monthly electricity consumption for the selected countries have not yet been published in Eurostat. Therefore, the electricity generation results could not be compared with the consumption results.
- Nuclear energy does not yet contribute to electricity generation in Turkey. Additionally, Spain and the UK have no geothermal power plants. Therefore, total renewable and non-renewable sources were evaluated in this study.
- The ML methods include the support vector machines technique, for which 50% of the data are taken for the training process. This ratio can be increased and could affect the accuracy of the model but also lead to overfitting. Future studies can make these changes and compare the results.

For further studies, the seasonal fluctuation technique can be used with other popular grey prediction models (e.g., fractional multivariable grey prediction models or conformable fractional grey models) to compare the results of the prediction models. Additionally, monthly or quarterly energy consumption of countries or cities before and after the Covid-19 lockdown can be evaluated with the forecasting tools used in this study. Therefore, this study opens up new avenues for researchers to investigate these topics. Moreover, during the Covid-19 pandemic lockdown, the most significant declines in the electricity generation of the selected countries were from non-renewables. This situation shows that increasing the share of renewable energy sources in the total electricity generation of countries may more reliably meet electricity demand.

CRediT authorship contribution statement

Utkuçan Şahin: Supervision, Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft, Investigation, Data curation, Writing – review & editing. Serkan Ballı: Methodology, Software, Validation, Formal analysis, Writing – review & editing. Yan Chen: Methodology, Software, Validation, Formal analysis, 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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