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Research article

Future of renewable energy consumption in France, Germany, Italy, Spain, Turkey and UK by 2030 using optimized fractional nonlinear grey Bernoulli model

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ABSTRACT

In this study, gross final energy consumption (GFEC), energy consumption of renewable energy sources (RES) and its share in France, Germany, Italy, Spain, Turkey and the United Kingdom (UK) are forecasted by 2030. A novel model is proposed in this study which is called optimized fractional nonlinear grey Bernoulli model, briefly as OFANGBM(1,1). In this model, three parameters, which are background value λ, power index value γ and fractional order value r, are optimized by genetic algorithm (GA) method. Results of OFANGBM(1,1) show that GFEC in France, Germany, Italy, Spain, Turkey and UK will reach to 151.7 Mtoe, 227.6 Mtoe, 110.8 Mtoe, 84.5 Mtoe, 173.4 Mtoe and 132.2 Mtoe, respectively, in 2030. Additionally, energy consumption from RES in France, Germany, Italy, Spain, Turkey and UK is forecasted as 28.5 Mtoe, 53.8 Mtoe, 22.2 Mtoe, 23.2 Mtoe, 26.1 Mtoe and 39.3 Mtoe, respectively, for the year 2030. Results of this study are compared with the national target of these countries on the share of RES in GFEC. Moreover, it is estimated that RES can satisfy 18.8%, 23.6%, 20.0%, 27.5%, 15.1% and 29.7% of GFEC in France, Germany, Italy, Spain, Turkey and UK in 2030, respectively.

1. Introduction

While the need of energy increases, conventional sources are rapidly running out. To overcome this handicap, renewable energy sources with their advantages are an alternative way for governments' energy strategy (Pacesila et al., 2016). In 2017, World final energy consumption was reported as 9717 Mtoe with a growth rate of 1.9% and the European countries had the share of 14.5% in World final energy consumption (IEA, 2020). In 2018, gross final energy consumption among the European countries was the highest in Germany (223.3 Mtoe), followed by the France (154.5 Mtoe), the United Kingdom (UK) (133.7 Mtoe), Italy (121.5 Mtoe), Turkey (105.0 Mtoe) and Spain (89.2 Mtoe), respectively (Eurostat, 2020a). Additionally, the share of renewable sources in gross final energy consumption in the European Union (EU) reached from 8.5% in 2004 to 18.0% in 2018. The EU targets to raise this share up to 20% by 2020 and 32% by 2030 (Eurostat, 2020b). Forecasting of this target has been subject to many researchers (Knopf et al., 2015; Nikolaev and Konidari, 2017; Liobikiene and Butkus, 2017; Cucchiella et al., 2018; Mehedintu et al., 2018; Simionescu et al., 2020). Forecasting of energy consumption plays a key role of energy management (Wei et al., 2019). Even since the last two years, grey prediction models have been widely used as a forecasting tool by many researchers in this field (Li and Zhang, 2019; Zhang et al., 2019; Ye et al., 2019; Wang and Song, 2019; Wang et al., 2019; Lu, 2019; Wang et al., 2020; Ma and Wang, 2020).

The simplest form of grey prediction models is GM(1,1), firstly proposed by Deng (Deng, 1982). The main advantage of this model is that it can be used to predict a small number of sequence data (Liu et al., 2016). The methodology of GM(1,1) is based on the first-order single variable prediction (Ma et al., 2013) and this method was used in forecasting of energy by researchers (Yuan et al., 2016; Tsai, 2016; Li and Li, 2017; Şahin, 2018). The GM(1,1) assumes that the background value (λ) is equal to 0.5, but researchers have tried to optimize the parameter λ which is in the range of 0-1 and is called optimized grey prediction model, briefly as OGM(1,1). Many studies (Wen et al., 2000; Shang and Pei, 2009; Zhou et al., 2009; Zhao et al.,2012; Ma et al., 2013; Ene and Öztürk, 2017) showed that the OGM(1,1) presents higher prediction performance than GM(1,1). Multivariable grey models are the other improved forms of the GM(1,1) and the basic multivariable grey model is GM(1,N), where N denotes the number of variables of the modeling equation (Hsu and Wang, 2009). Hsu and Wang (2009) showed the GM(1,N) gives higher prediction performance than GM(1,1). Hsu (2009) and Zhong et al. (2017) investigated the prediction performance due to the optimization of the parameter λ in GM(1,N). The optimized

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Nomenclatures

AAGR	average annual growth rate (%)s
AGO	accumulated generating operation
APE	absolute percentage error (%)
GM(1,1)	basic grey model
FANGBM(1,1)	fractional nonlinear grey Bernoulli model
MAPE	mean absolute percentage error (%)
NGBM(1,1)	nonlinear grey Bernoulli model
OGM(1,1)	optimized grey model
ONGBM(1,1)	optimized nonlinear grey Bernoulli model
OFANGBM(1,1)	optimized fractional nonlinear grey Bernoulli model
λ	background value
γ	power index value
r	fractional order value

GM(1,N) is called as OGM(1,N) (Hu, 2020). Tien (2005) proposed grey prediction model with convolution integral (GMC(1,N)) to improve the traditional GM(1,N). Wang (2015) showed that the MAPE value of the GMC(1,N) is lower than that of the GM(1,N). Then, the background value λ of GMC(1,N) is optimized by Wang and Hao (2016) for the prediction of industrial energy consumption in China and the model is named as OGMC(1,1). Additionally, effect of optimization of the parameter λ on prediction performance has been investigated in the another grey model which is based on "rolling" or "metabolism" technique. The main advantage of this technique is that this method gives better prediction results using the latest data sequence (Chang et al., 2005). When the rolling mechanism technique is used in GM(1,1), the model is called metabolic grey model, briefly as MGM(1,1). Many studies showed that the MGM(1,1) presents more accurate results than the GM(1,1) (Zhao et al.,2012; Ma et al., 2013; Boran, 2015; Zhao et al., 2016; Zhao and Guo, 2016; Wang et al., 2017). Also, researchers have improved the MGM(1,1) by optimizing the parameter λ and the improved model is called optimized metabolic grey model, briefly as OMGM(1,1). There are many studies that the OMGM(1,1) gives higher prediction performance than the MGM(1,1) (Zhao et al.,2012; Ma et al., 2013; Liu et al., 2014; Wang et al., 2017; Li et al., 2018; Şahin, 2019). In the further studies, researchers investigated the nonlinearity of MGM(1,1) and the model is called nonlinear metabolic grey model, briefly as NMGM(1,1). The biggest difference between the NMGM(1,1) and MGM(1,1) is that the NMGM(1,1) has characterized with the power coefficient value (α) which denotes the nonlinearity (An et al., 2019). Wang et al. (2018) and Şahin (2019) showed that NMGM(1,1) gives higher prediction performance than MGM(1,1). Şahin (2019) has improved the NMGM(1,1) by optimizing the parameter λ and the model is called optimized nonlinear metabolic grey model (ONMGM(1,1)) and compared these models for the for the forecasting of Turkey's greenhouse gas emissions. The results show that mean absolute percentage error (MAPE) of the NMGM(1,1) is lower than that of the MGM(1,1) which means NMGM(1,1) gives higher prediction results than MGM(1,1) for this study. The another improved grey model is nonlinear grey Bernoulli model (NGBM(1,1)) which is proposed by Chen (Chen, 2008). In this model, power index value (γ) is used to fit the curve of actual data. When γ is equal to 0, the NGBM(1,1) reduces to the GM(1,1) (Wu et al., 2019a). Researchers show that the NGBM(1,1) gives higher prediction performance than the GM(1,1) (Chen, 2008; Chen et al., 2008; Chen et al., 2010; Hsu, 2010; Tsai, 2016; Pei and Li, 2019; Wu and Zhang, 2020). Chen et al. (2008) improved the NGBM(1,1) by optimizing the background value (λ) and the improved model is called optimized nonlinear grey Bernoulli model (ONGBM(1,1) or Nash nonlinear grey Bernoulli model (NNGBM(1,1)) (Chen et al., 2010). Many studies present that the optimized NGBM(1,1) gives a higher accuracy than that of the traditional NGBM(1,1) (Chen et al., 2008; Zhou et al., 2009; Chen et al., 2010; Wang et al., 2011; Wang, 2013; Lu et al., 2016). Also recently, NGBMC(1,n) and NGBM(1,1,k,c) have been proposed as improved versions of the NGBM(1,1) by Ma et al. (2019a) and Wu et al. (2020), respectively. Table 1 summarizes effect of optimizing the background value λ in the grey prediction models, mentioned in the literature review above, on the MAPE values. It is obvious that the background value λ value varying from 0 to 1 instead of 0.5 in grey prediction models improves the prediction accuracy.

In addition to the above grey prediction models, a new technique "fractional order accumulation" is firstly applied into the GM(1,1) by Wu et al (2013). The novel model, is called fractional grey prediction model, inspired many researchers due to its superior predictive performance, especially used as a forecasting tool in energy researches. Fractional grey prediction models have been applied to predict China's electricity consumption (Yang and Xue, 2016), China's nuclear energy consumption (Wu et al., 2018), China's crude oil consumption (Duan et al., 2018), China's wind energy consumption (Zhang et al., 2019), China's natural gas and coal consumption (Ma et al., 2019b), renewable energy consumption in China (Wu et al., 2019a), China's energy consumption (Wu et al., 2019b), natural gas consumption of countries (Ma et al., 2020), Turkey's electricity generation and installed capacity (Şahin, 2020) and China's annual electricity consumption (Xie et al., 2020). Recently, Wu et al. (2019) firstly applied fractional order accumulation into the nonlinear grey Bernoulli model and the new model is called as fractional nonlinear grey Bernoulli model, briefly as FANGBM(1,1). The prediction performance of the FANGBM(1,1) depends on optimizing the two parameters which are power index value (γ) and fractional order value (r). These two parameters characterize the model's ability to adapt to actual data. Then, Şahin, 2020 used the FANGBM(1,1) to forecast Turkey's electricity generation and installed capacity from total renewable and hydro energy. In another study (Şahin and Şahin, 2020), this model was used to forecast the cumulative number of confirmed cases of COVID-19 in many countries. In these studies, the background value λ of FANGBM(1,1) is equal to 0.5.

When the above-mentioned literature is carefully reviewed, the idea that FANGBM(1,1) can be improved by optimizing the background value λ has emerged. This study proposed a novel model which is called as optimized fractional nonlinear grey Bernoulli model, abbreviated as OFANGBM(1,1). In the novel model, effect of optimizing λ on the prediction performance is investigated.

Moreover, fractional grey prediction models can be used to forecast the renewable energy consumption and total energy consumption for European countries due to their high prediction performance. In this way, projections on the share of renewable sources in energy consumption for these countries can be made and provide information on how far to approach future targets. As far as the author's knowledge, EU's target on the share of renewable sources in gross final energy consumption has not forecasted yet by using fractional grey prediction models. As a result, it is believed that this study fills the gap in the literature. Therefore, this study aims to forecast renewable energy consumption and gross final energy consumption of selected European countries, which are Germany, France, Italy, Spain, Turkey and the United Kingdom using FANGBM(1,1) and OFANGBM(1,1) by 2030. The reason for these countries being selected is the highest gross final energy consumption in European countries for the year 2018, according to the data of Eurostat.

The novelty of this study is an improved fractional nonlinear grey Bernoulli model is proposed. The difference of the new proposed model from the FANGBM(1,1) is that the background value

Table 1
The overview of comparison of MAPE values between grey prediction models and optimized grey prediction models in the literature.

Reference	Study	Grey prediction models	MAPE (%)
Wen et al., 2000	Cage-net amounts of fish	GM(1,1)	10.32
		OGM(1,1)	7.86
Shang and Pei, 2009	Chinese rural gross domestic product	GM(1,1)	4.45
		OGM(1,1)	4.06
Ene and Öztürk, 2017	End-of-life vehicles of West Anatolia region	GM(1,1)	4.83
		OGM(1,1)	4.62
Hsu, 2009	Taiwan's integrated circuit industry output	GM(1,N)	0.29
		OGM(1,N)	0.24
Zhong et al., 2017	Photovoltaic power generation (for April)	GM(1,N)	3.53
		OGM(1,N)	7.14
Wang and Hao, 2016	Industrial energy consumption in China	GMC(1,N)	11.24
		OGMC(1,N)	8.34
Zhou et al., 2009	Power load of Hubei electric power network	GM(1,1)	3.63
		OGM(1,1)	3.61
		NGBM(1,1)	1.79
		ONGBM(1,1)	1.78
Zhao et al., 2012	Per capita annual net income of rural households in China	GM(1,1)	8.29
		OGM(1,1)	7.88
		MGM(1,1)	4.69
		OMGM(1,1)	2.79
Ma et al., 2013	Iron ore import of China	GM(1,1)	16.88
		OGM(1,1)	14.45
		MGM(1,1)	6.70
		OMGM(1,1)	2.31
Liu et al., 2014	Financial intermediation in Beijing	MGM(1,1)	8.36
		OMGM(1,1)	0.05
	Real estate in Beijing	MGM(1,1)	61.77
		OMGM(1,1)	0.99
	Semiconductor industry production in Beijing	MGM(1,1)	10.52
		OMGM(1,1)	8.38
Wang et al., 2017	Beijing's tertiary industry	GM(1,1)	4.54
		OGM(1,1)	4.05
		MGM(1,1)	4.54
		OMGM(1,1)	0.07
	Beijing's other services industry	GM(1,1)	12.11
		OGM(1,1)	11.22
		MGM(1,1)	8.04
		OMGM(1,1)	0.12
Li et al., 2018	Spontaneous combustion of the stockpiled coal	MGM(1,1)	1.83
		OMGM(1,1)	0.50
Şahin, 2019	Turkey's GHG emissions from the energy sector	MGM(1,1)	5.55
		OMGM(1,1)	5.26
		NMGM(1,1)	5.25
		ONMGM(1,1)	5.19
Wang et al., 2011	Opto-electronics components in Taiwan	NGBM(1,1)	4.82
		ONGBM(1,1)	4.04
	Opto-electronics application in Taiwan	NGBM(1,1)	4.10
		ONGBM(1,1)	3.10
Lu et al., 2016	Foreign exchange rates in Taiwan	NGBM(1,1)	0.25
		ONGBM(1,1)	0.10

(λ) is also optimized in the range of 0-1. Therefore, it is aimed that having more accurate results than that of the FANGBM(1,1) by optimizing three parameters are λ, γ and r.

The main contributions of this study can be given as:

(1) The background value λ of the FANGBM(1,1) is equal to 0.5. However, in many improved grey prediction models, which are OGM(1,1), OMGM(1,1), ONMGM(1,1) and NNGBM(1,1), this parameter is in the range of 0-1. This phenomena can be used in the FANGBM(1,1). In other words, the FANGBM(1,1) can be improved by optimizing the parameter λ and as far as the author's knowledge, this issue is probably the first in the literature. In this study, a new model is proposed which is called optimized fractional nonlinear grey Bernoulli model, briefly as OFANGBM(1,1).

(2) In the OFANGBM(1,1), the background value (λ), power index value (γ) and fractional order value (r) are optimized by using genetic algorithm (GA) technique for this study. In this way, the proposed model with higher prediction performance can be used for the further studies.

(3) The OFANGBM(1,1) is used to forecast the renewable energy consumption, gross final energy consumption and its share in Germany, France, UK, Italy and Turkey by the year 2030. Except for the previous studies (Cucchiella et al., 2018; Mehedintu et al., 2018;Simionescu et al., 2020), forecasting on this issue is very scarce in the literature whereas these studies present projections by the year 2020. This study not only tests the national targets of the selected countries in 2020, but also provides projections on this issue by 2030.

(4) The results of this study are expected to provide important information to researchers and energy decision makers.

The rest of this study is: In Section 2, the methodology of the OFANGBM(1,1) is given. Additionally, the optimization technique and how the prediction performance is measured is mentioned. In Section 3, the results of this study are presented and also compared with the literature. Finally, Section 4 presents the conclusions, suggestions and limitations.

2. Methodology

This section presents the methodology of the proposed novel model, optimized fractional nonlinear grey Bernoulli model (OFANGBM(1,1)). Additionally, the cycle scheme on how the OFANGBM(1,1) reduces to GM(1,1) is mentioned. At the end of this section, how the optimal parameter is obtained and which metric is used for evaluating performance are given.

2.1. The structure of optimized fractional nonlinear grey Bernoulli model

The principle of fractional order accumulated is based on the r-th accumulated generation operation (r-AGO) and Wu et al. (2013) presented this methodology with the following definitions.

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

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \ \ldots\ldots.., X^{(0)}(n), \ \mathrm{n} \geq 4 \right\} \quad (1)$$

$X^{(0)}$ transforms to the $X^{(r)}$ as:

$$X^{(\mathrm{r})} = \left\{X^{(\mathrm{r})}(1), X^{(\mathrm{r})}(2), X^{(\mathrm{r})}(3), \ \ldots\ldots.., X^{(\mathrm{r})}(n)\right\} \quad (2)$$

Where $X^{(r)}$ is the r-th accumulated generating operation (r-AGO) sequence of $X^{(0)}$ and r denotes the fractional order value $r > 0$. Additionally, $X^{(r)}$ can be formulated as:

$$X^{(\mathrm{r})}(k) = \sum_{i=1}^{k} X^{(r-1)}(i) = \sum_{i=1}^{k} \binom{k-j+r-1}{k-j} X^{(0)}(i), \ k = 1, 2, \ldots.., n \quad (3)$$

where

$$\binom{k-j+r-1}{k-j} = \frac{(r+k-i-1)(r+k-i-2)(r+k-i-3)\ldots(r+1)r}{(k-i)!} \quad (4)$$

When $r = 1$, $X^{(r)}(k)$ reduces to $X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i)$ which denotes the first-order accumulated generating operation (1-AGO) sequence of $X^{(0)}$.

Wu et al. (2019a) presented the whitening equation of fractional nonlinear grey Bernoulli model (FANGBM(1,1)) as:

$$\frac{dX^{(\mathrm{r})}(k)}{dt} + aX^{(\mathrm{r})}(k) = b\left(X^{(\mathrm{r})}(k)\right)^{\gamma} \quad (5)$$

and the discrete form can be given as,

$$X^{(\mathrm{r})}(k) - X^{(\mathrm{r})}(k-1) + az^{(\mathrm{r})}(k) = b\left(z^{(\mathrm{r})}(k)\right)^{\gamma} \quad (6)$$

where γ indicates the power index value.

When $r = 1$, the whitening equation and the discrete form can be written respectively, as (Lu et al., 2016):

$$\frac{dX^{(1)}(k)}{dt} + aX^{(1)}(k) = b\left(X^{(1)}(k)\right)^{\gamma} \quad (7)$$

$$X^{(1)}(k) - X^{(1)}(k-1) + az^{(1)}(k) = b\left(z^{(1)}(k)\right)^{\gamma} \quad (8)$$

and this model is called the nonlinear grey Bernoulli model, briefly as NGBM(1,1)), firstly proposed by Chen (2008).

When $\gamma = 0$ and $r = 1$, the whitening equation and the discrete form can be presented by the following equations (Wu e al., 2019a),

$$\frac{dX^{(1)}(k)}{dt} + aX^{(1)}(k) = b \quad (9)$$

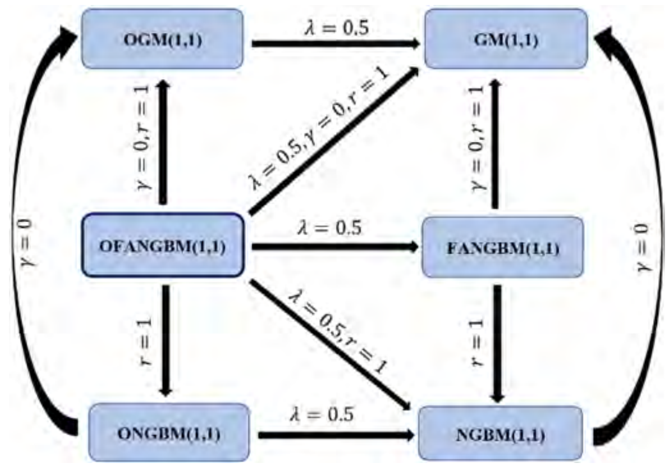

Fig. 1. Cyclic scheme of the grey prediction models for this study.

$$X^{(1)}(k) - X^{(1)}(k-1) + az^{(1)}(k) = b \quad (10)$$

and this model is called the grey model, briefly as GM(1,1), firstly proposed by Deng (1982).

In Eq. (6), the form of $z^{(r)}(k)$ is given by (Mao et al., 2016) as:

$$z^{(\mathrm{r})}(k) = \lambda * X^{(\mathrm{r})}(k) + (1-\lambda) * X^{(\mathrm{r})}(k-1), \ k = 2, 3, 4, \ldots.., n \quad (11)$$

where λ denotes the background value which is which is in the range of 0-1 (Ma et al., 2013). In FANGBM(1,1), the background value λ is equal to 0.5 (Wu et al., 2019a). When λ is in the range of 0-1, the model is called the optimized nonlinear fractional grey Bernoulli model, abbreviated as OFANGBM(1,1) in this study. Therefore, constraints of the parameters of the OFANGBM(1,1) can be given as $0 < \lambda < 1$, $\gamma \neq 0$, and $r > 0$.

Additionally, when λ ranges from 0 to 1 in the Eq. (8) and (10), the model is called as optimized nonlinear grey Bernoulli model (ONGBM(1,1)) and optimized grey model (OGM(1,1)), respectively. This cycle can be summarized in Fig. 1. By this way, it is explained that how the OFANGBM(1,1) reduces to GM(1,1) with the changing of parameters λ, γ and r.

Once given the background value (λ), power index value (γ) and fractional order value (r), parameters a and b of the whitening equation of grey prediction models can be calculated by the least squares method as:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left[B^T B\right]^{-1} B^T Y \quad (12)$$

where

$$\mathrm{B} = \begin{bmatrix} -z^{(\mathrm{r})}(2) & \left(z^{(\mathrm{r})}(2)\right)^{\gamma} \\ -z^{(\mathrm{r})}(3) & \left(z^{(\mathrm{r})}(3)\right)^{\gamma} \\ -z^{(\mathrm{r})}(4) & \left(z^{(\mathrm{r})}(4)\right)^{\gamma} \\ \vdots & \vdots \\ \vdots & \vdots \\ -z^{(\mathrm{r})}(\mathrm{n}) & \left(z^{(\mathrm{r})}(\mathrm{n})\right)^{\gamma} \end{bmatrix}$$

$$Y = \begin{bmatrix} X^{(\mathrm{r})}(2) - X^{(\mathrm{r})}(1) \\ X^{(\mathrm{r})}(3) - X^{(\mathrm{r})}(2) \\ X^{(\mathrm{r})}(4) - X^{(\mathrm{r})}(3) \\ \vdots \\ \vdots \\ X^{(\mathrm{r})}(n) - X^{(\mathrm{r})}(n-1) \end{bmatrix} \quad (13)$$

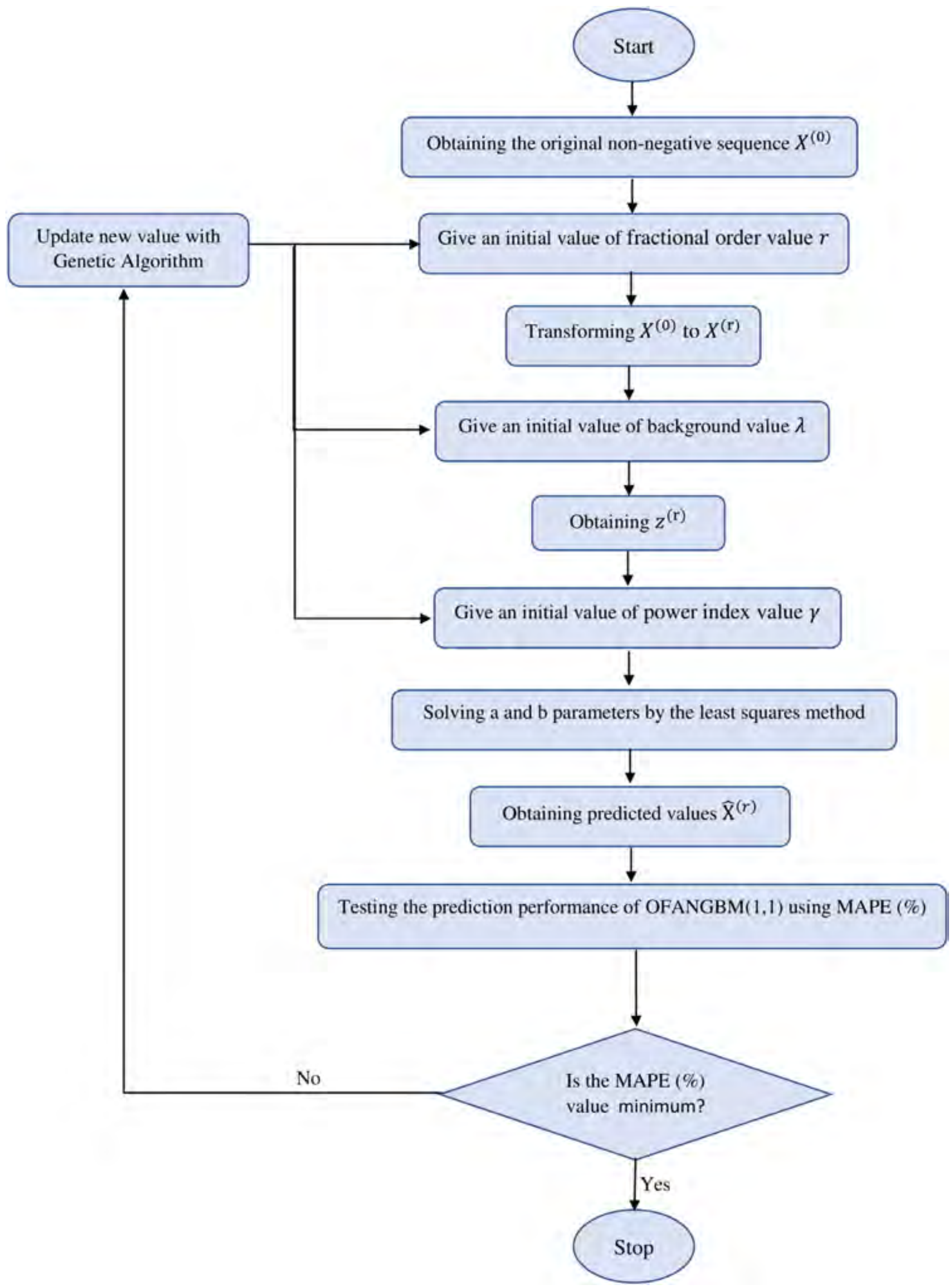

Fig. 2. The flowchart scheme of the OFANGBM(1,1) in this study.

Finally, the predicted values can be calculated by the following equations:

$$\begin{cases} \hat{X}^{(r)}(1) = X^{(0)}(1) \\ \hat{X}^{(r)}(k) \\ = \left[\left(\left(\hat{X}^{(r)}(1) \right)^{1-\gamma} - \frac{b}{a} \right) e^{-a*(1-\gamma)(k-1)} + \frac{b}{a} \right]^{\frac{1}{1-\gamma}} \end{cases}, \quad k = 2, 3, \ldots, n \tag{14}$$

2.2. Optimization of the parameters and metrics for evaluating performance

In this study, finding the optimal value of the parameters is based on reaching the smallest mean absolute percentage error (MAPE) value of the prediction model. To achieve this, genetic algorithm (GA) method is used which has been widely used as an optimization technique in literature (Wang and Hsu, 2008; Hsu, 2009; Hsu, 2010). The GA is solved by installing a software package on the Microsoft Excel for this study and runtime is continued until the change of the MAPE value reaches to 0.01% in the simulation process.

In this study, the error between the original data and predicted data is obtained by calculating of the absolute percentage error (APE). Additionally, prediction performance between FANGBM(1,1) and OFANGBM(1,1) is compared by using MAPE. The formulation of the APE and MAPE is given by the following equation (Ding et al., 2020):

$$APE\ (\%) = \left| \frac{X(i) - \hat{X}(i)}{X(i)} \right| x100 \tag{15}$$

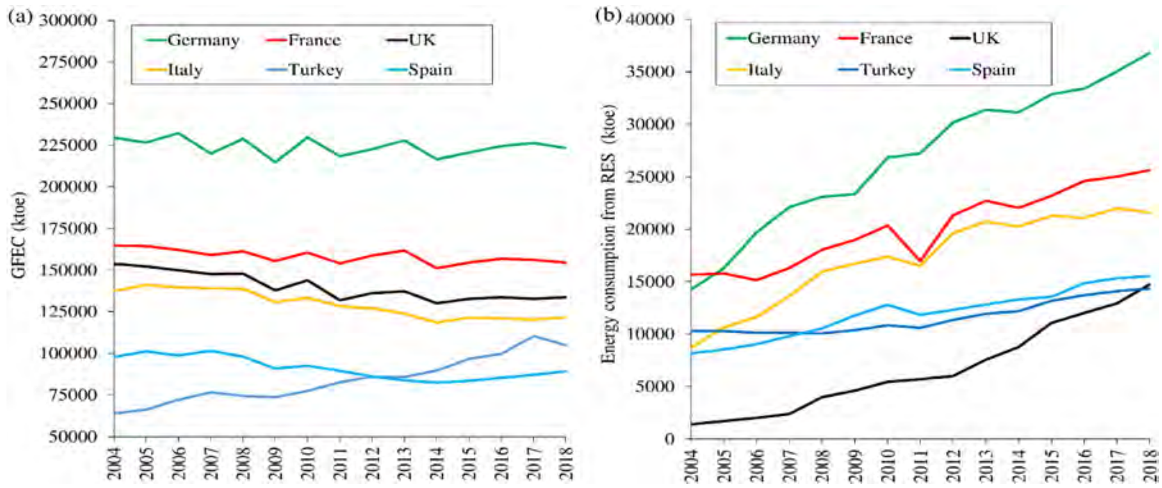

Fig. 3. Actual values of GFEC (a) and energy consumption from RES (b) for the selected countries from 2004 to 2018.

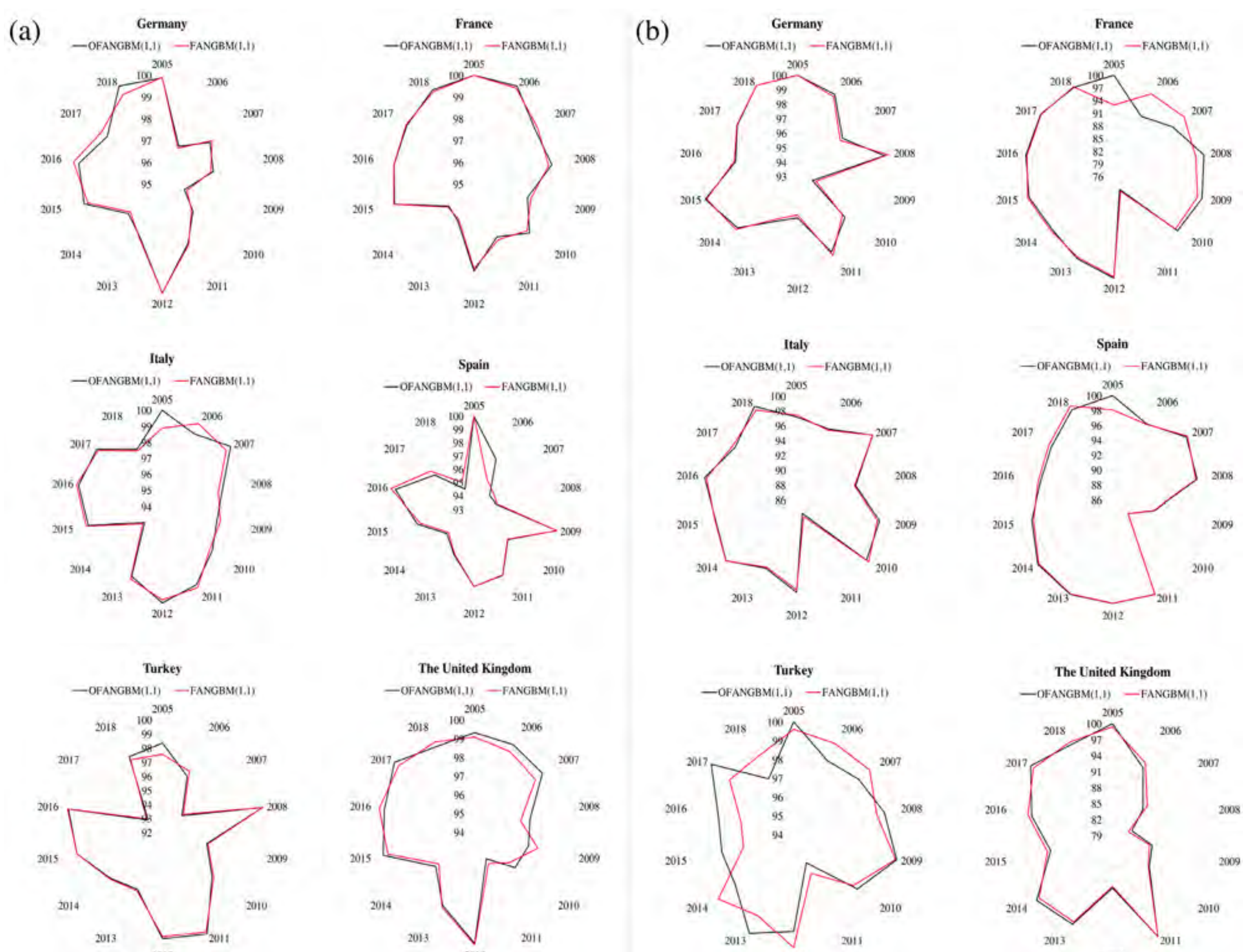

Fig 4. Goodness of fit values of FANGBM(1,1) and OFANGBM(1,1) for the prediction of gross final energy consumption (a) and energy consumption from RES (b) in the selected countries.

$$MAPE\ (\%) = \sum_{i=2}^{n} \left| \frac{X(i) - \hat{X}(i)}{X(i)} \right| x \frac{100}{n-1} \tag{16}$$

Where, X is the actual data, $\hat{X}$ is the predicted data and n is the observation data. The lowest MAPE value denotes the best prediction model in this study and the prediction model is classified as high level when MAPE value is lower than 10% (Lewis, 1982). Additionally, goodness of fit values for the grey prediction models can be formulated as (Han and Li, 2019):

$$Goodness\ (\%) = 100 - APE(\%) \tag{17}$$

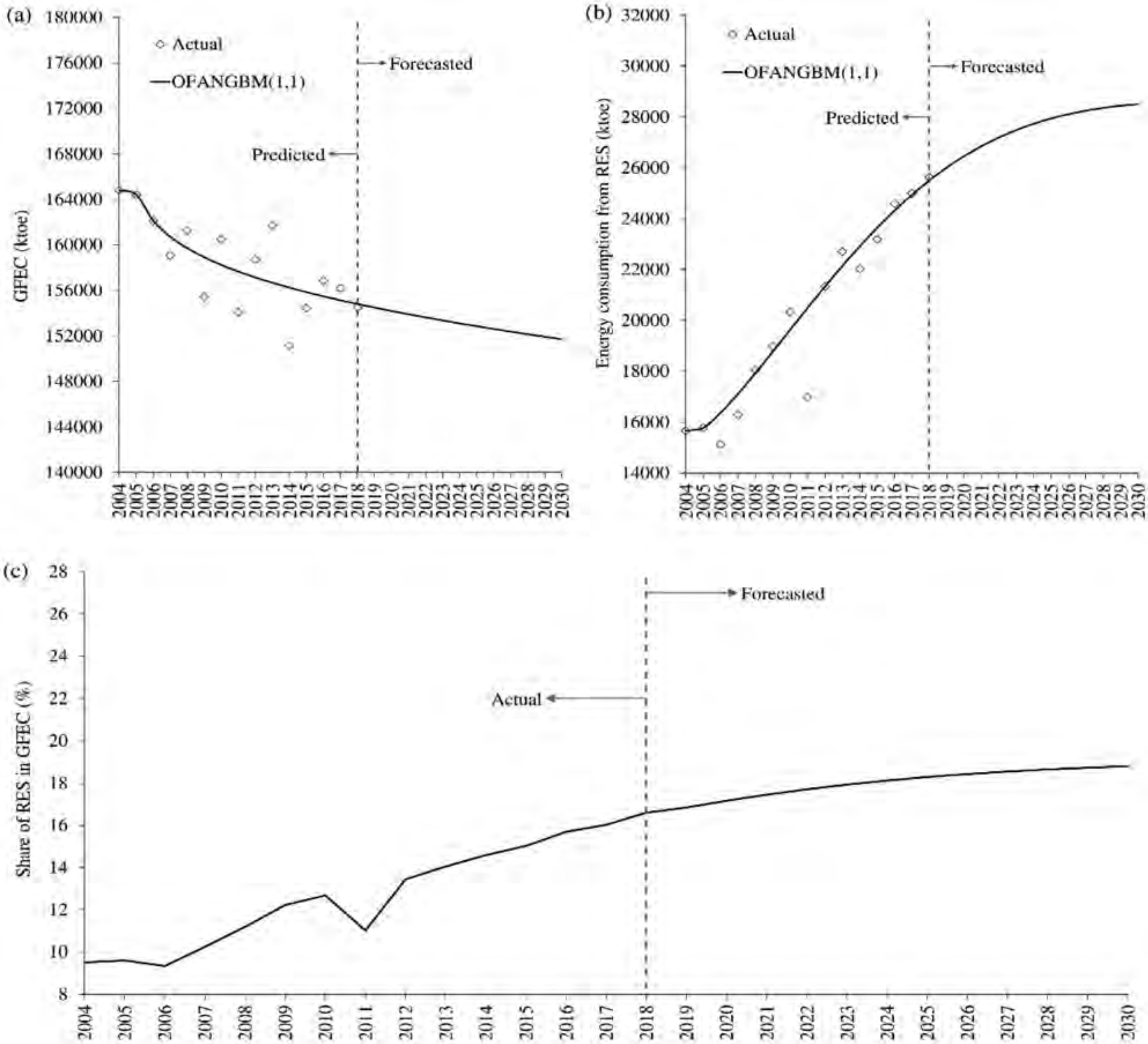

Fig 5. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in France by 2030.

The flowchart scheme of the OFANGBM(1,1) for this study is presented in Fig. 2.

3. Results and discussions

This section presents the prediction results of fractional nonlinear grey Bernoulli model (FANGBM(1,1)) and optimized fractional nonlinear grey Bernoulli model (OFANGBM(1,1)). Additionally, comparison of the mean absolute percentage error (MAPE) values and goodness of fit between FANGBM(1,1) and OFANGBM(1,1) for the selected countries are given. Furthermore, forecasting results of FANGBM(1,1) and OFANGBM(1,1) for gross final energy consumption, renewable energy consumption and its shares in the selected countries are presented and compared with the literature.

3.1. Data description

In this study, two indicators, which are energy consumption of renewable sources and gross final energy consumption (GFEC), are evaluated for the prediction and forecasting. Renewable energy sources (RES) consist of hydro, wind, geothermal energy and all forms of biomass (Eurostat, 2020b). GFEC denotes the energy supplied in households, industry, services including public services, transport, agriculture, forestry and fisheries, including the consumption of electricity and heat by the energy branch for electricity and heat production and including losses of electricity and heat in distribution and transmission (European Commission, 2020). The statistical data of GFEC and energy consumption of RES is taken from the database of Eurostat (Eurostat, 2020a). In this study, France, Germany, Italy, Spain, Turkey and the United Kingdom (UK) are selected because of having the highest GFEC in European countries for the year 2018. The data of GFEC and energy consumption of RES is available from the year 2004 to 2018 for these countries and is presented in Fig. 3.

3.2. Comparison of prediction performance

By using genetic algorithm method, optimal parameters of FANGBM(1,1) and OFANGBM(1,1) in prediction of gross final energy

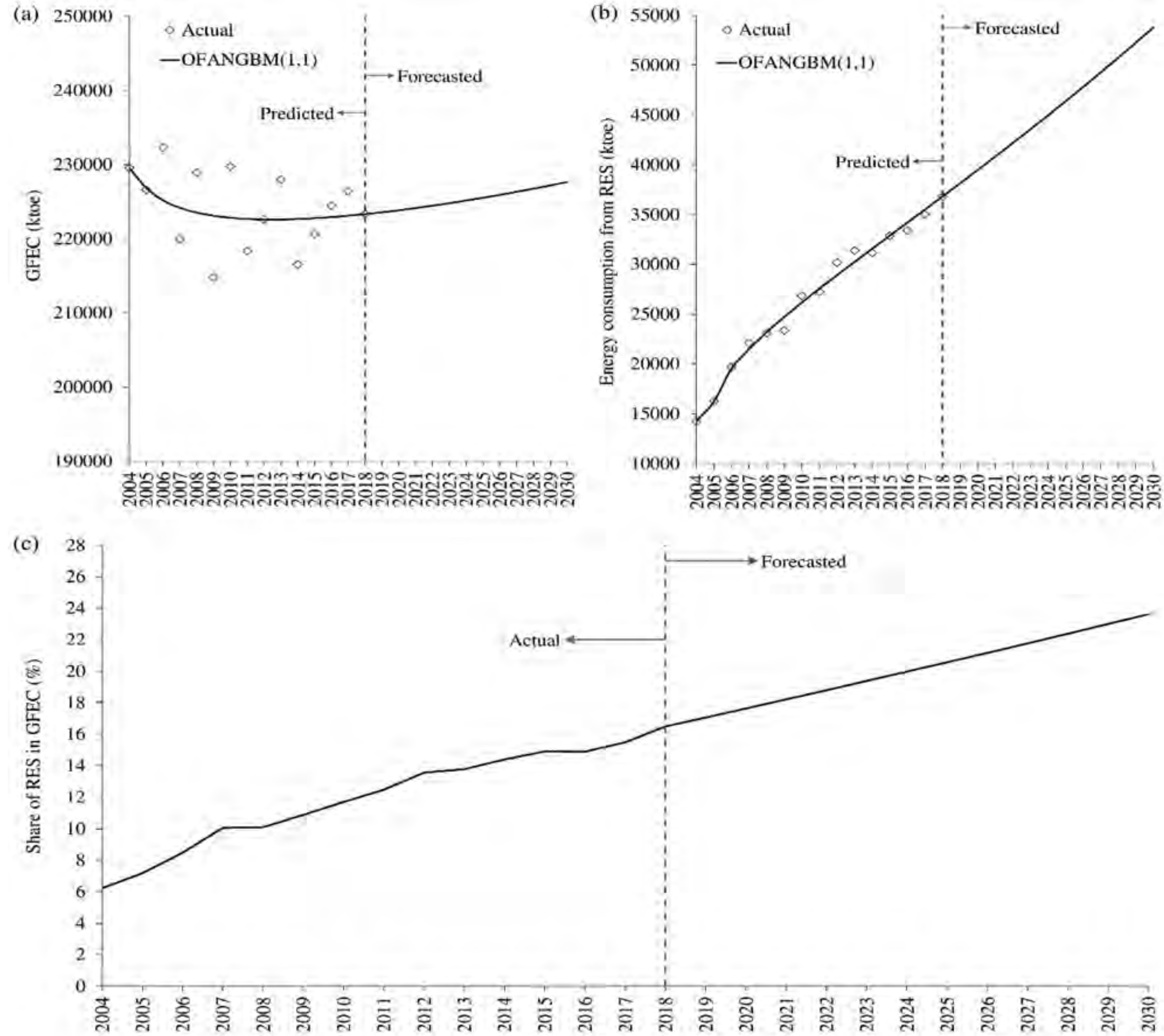

Fig 6. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in Germany by 2030.

consumption (GFEC) and energy consumption from RES in France, Germany, Italy, Spain, Turkey and UK are obtained and listed in Table 2. Notice that the background value λ of OFANGBM(1,1) is in the range of 0-1 whereas this value is equal to 0.5 in FANGBM(1,1). The optimal parameters of FANGBM(1,1) and OFANGBM(1,1) are obtained according to mean absolute percentage error (MAPE) of these grey prediction models reaches the smallest value in the simulation process.

By using Eq. (16), MAPE results of FANGBM(1,1) and OFANGBM(1,1) for the prediction of GFEC and energy consumption form RES in the selected countries are shown in Table 3. It is obvious that OFANGBM(1,1) has smaller MAPE values than that of FANGBM(1,1) in all cases which contributes to OFANGBM(1,1) presents higher prediction performance than FANGBM(1,1) for this study. Consequently, optimizing of the background value λ has improved the prediction performance of fractional grey prediction model as with other grey prediction model studies which is given in Table 1.

Additionally, goodness of fit values of FANGBM(1,1) and OFANGBM(1,1) for the prediction of GFEC and energy consumption from RES in the selected countries are presented in Fig. 4.

3.3. Forecasting results

In this section, forecasting results of OFANGBM(1,1) for GFEC, energy consumption from RES and its share in France, Germany, Italy, Spain, Turkey and UK are presented. Additionally, forecasting results of this study are discussed with the literature.

Fig. 5 presents the prediction and forecasting results of OFANGBM(1,1) for gross final energy consumption (GFEC), energy consumption from RES and its share in France. GFEC has decreased from 164.8 Mtoe in 2004 to 154.5 Mtoe in 2018. It is forecasted that GFEC will decrease to 151.7 Mtoe in 2030 with the average annual growth rate (AAGR) is -0.2% for the period 2018-2030 (Fig. 5a). Energy consumption from RES has increased from 15.7 Mtoe in 2004 to 25.6 Mtoe in 2018 and it is forecasted that this value will reach to 28.5 Mtoe in 2030 with the AAGR is 0.9% for the period 2018-2030 (Fig. 5b). Additionally, the share of RES in GFEC is estimated as 17.2% in 2020 and 18.8% in 2030 (Fig. 5c). The national target of France on this issue is equal to 23% in 2020 (Eurostat, 2020b). Moreover, this share in 2020 is estimated as 17.0-20.2% by Cucchiella et al. (2018) and 17.3% by

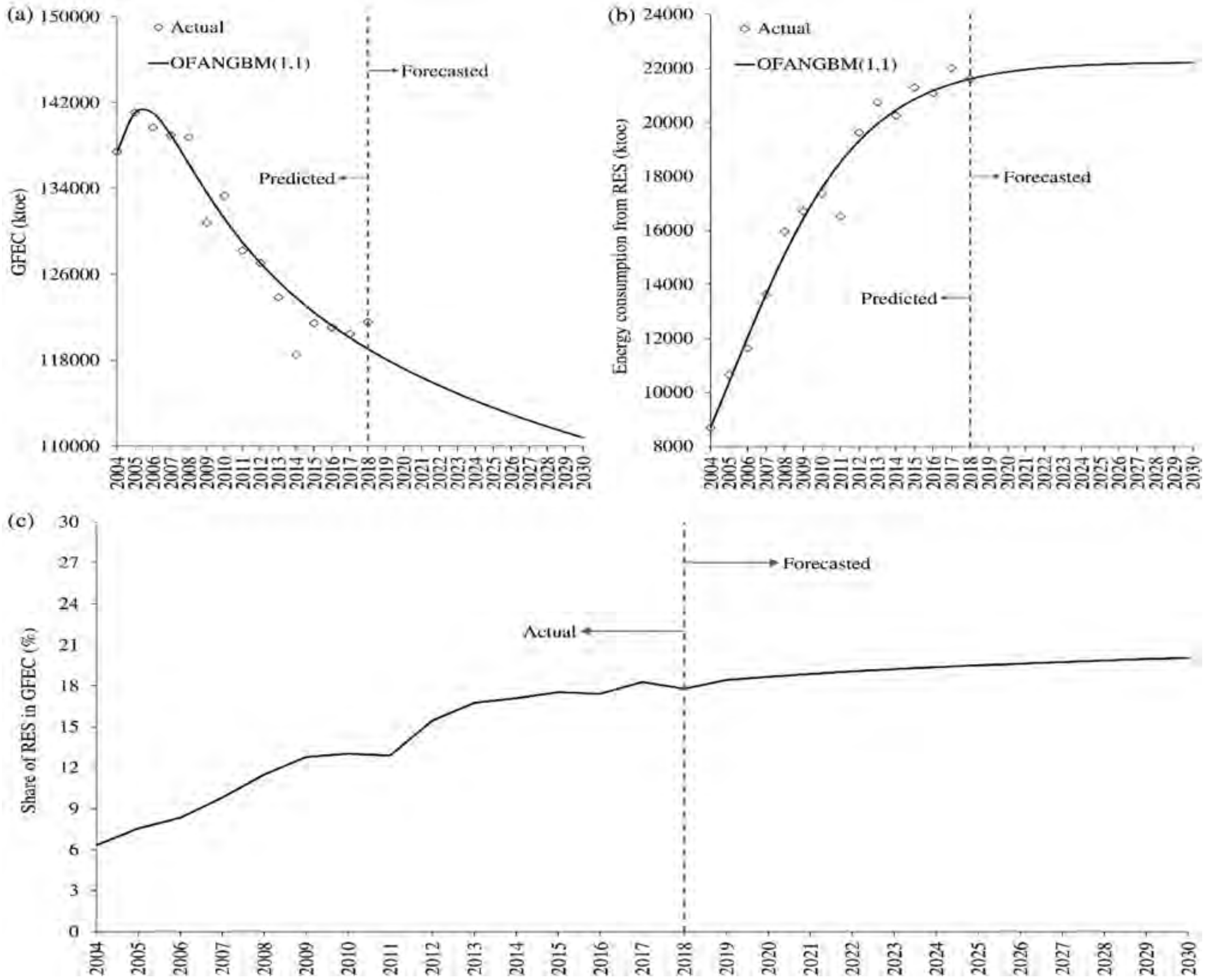

Fig 7. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in Italy by 2030.

Table 2
Optimal parameters of FANGBM(1,1) and OFANGBM(1,1) for this study.

Indicators	Countries	FANGBM(1,1)			OFANGBM(1,1)		
		λ	γ	r	λ	γ	r
GFEC	France	0.5	-0.4500	0.7134	0.5123	-0.4507	0.7095
	Germany	0.5	-28.3165	0.0587	0.4509	-26.8081	0.0567
	Italy	0.5	1.7061	0.1141	0.6960	-0.2663	0.1158
	Spain	0.5	0.5826	2.5499	0.5101	0.5527	2.3742
	Turkey	0.5	-1.4600	0.4168	0.4688	-1.5390	0.3890
	UK	0.5	-17.9968	1.00E-300	0.5718	-29.9451	3.06E-09
Energy consumption from RES	France	0.5	-0.1889	0.3129	0.3249	2.8733	0.0618
	Germany	0.5	0.5070	1.8237	0.4930	0.5083	1.8246
	Italy	0.5	1.4034	5.68E-300	0.4152	1.6750	1.00E-300
	Spain	0.5	-2.1037	0.1859	0.6442	0.2661	1.2838
	Turkey	0.5	-2.1429	0.4549	0.3671	-0.3025	0.9167
	UK	0.5	0.8124	0.1293	0.5727	0.6827	0.1371

Simionescu et al. (2020). Therefore, result of this study is consistent with the literature.

The prediction and forecasting results of OFANGBM(1,1) for gross final energy consumption (GFEC), energy consumption from RES and its share in Germany are presented in Fig. 6. Germany has the highest GFEC and energy consumption from RES values among the European countries in 2018. Especially, energy consumption from RES has increased from 14.3 Mtoe in 2004 to 36.8 Mtoe in 2018 with the AAGR is %7. OFANGBM(1,1) presents that this value will reach to 53.8 Mtoe in 2030 with the AAGR is 3.2% from 2018 to 2030 (Fig. 6b). The share of RES in GFEC is estimated as 17.6% in 2020 and 23.6% in 2030 is presented in Fig. 6c. The national target of Germany on this issue is equal to 18% in 2020 (Eurostat, 2020b). Additionally, the share of RES in GFEC in 2020 is estimated as 18.3-21.1% by Cucchiella et al. (2018) and 16.1% by Simionescu et al. (2020). Therefore, it can be said that OFANGBM(1,1) gives closer results to the target of Germany in 2020.

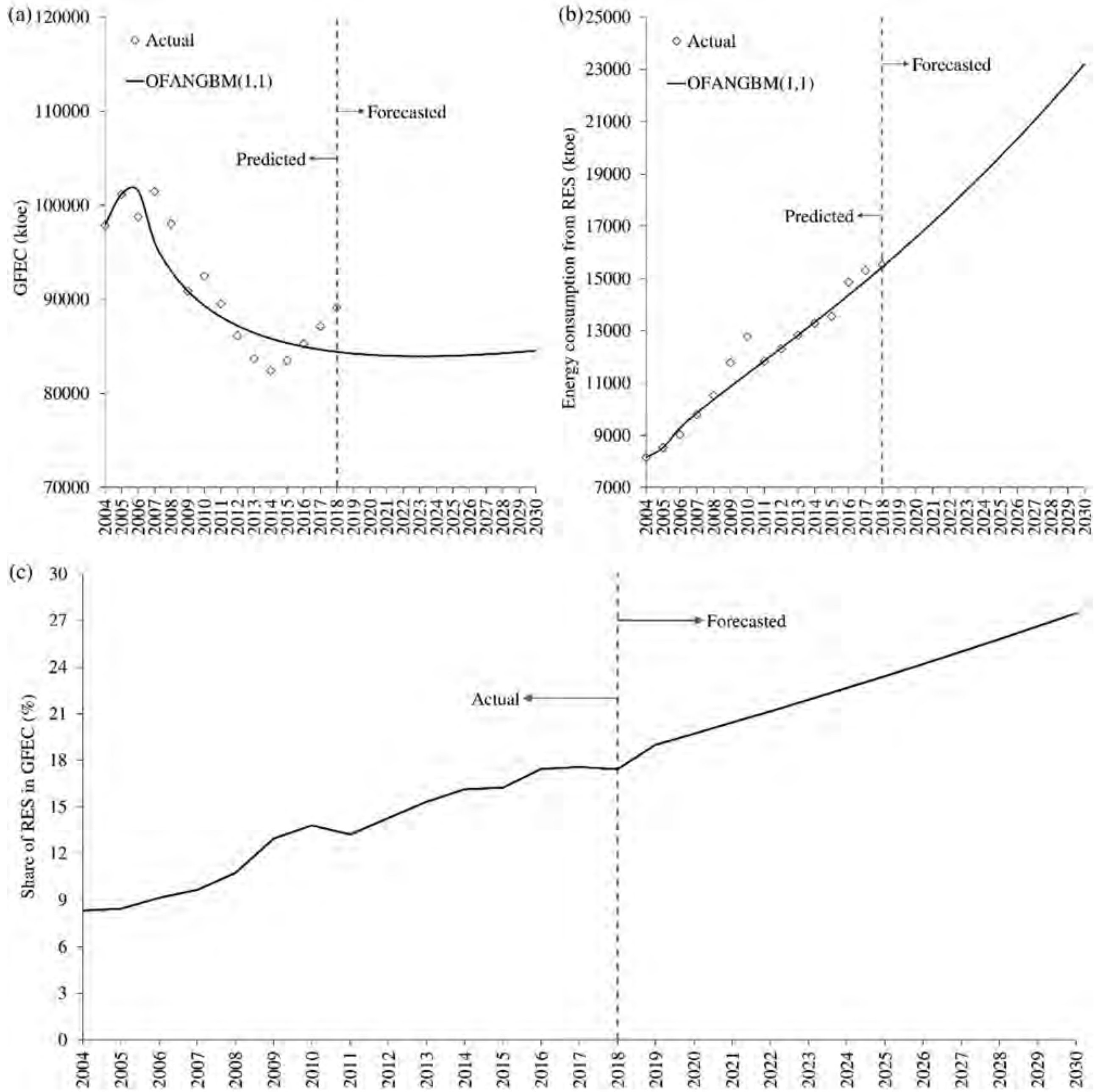

Fig 8. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in Spain by 2030.

Table 3
MAPE values of FANGBM(1,1) and OFANGBM(1,1) for this study.

Countries	Gross final energy consumption		Energy consumption from RES	
	FANGBM(1,1)	OFANGBM(1,1)	FANGBM(1,1)	OFANGBM(1,1)
France	1.3019	1.2943	3.6105	3.5362
Germany	1.7638	1.7588	1.8769	1.8707
Italy	1.1933	1.1476	2.7416	2.7139
Spain	2.7167	2.6893	2.4503	2.3551
Turkey	2.5699	2.5580	1.3287	1.3042
UK	1.6771	1.5780	6.5525	6.5416

Fig. 7 shows the prediction and forecasting results of OFANGBM(1,1) for GFEC, energy consumption from RES and its share in Italy. GFEC has decreased from 137.4 Mtoe in 2004 to 121.5 Mtoe in 2018. It is forecasted that GFEC will decrease to 110.8 Mtoe in 2030 with the AAGR is -0.8% for the period 2018-2030 (Fig. 7a). Energy consumption from RES has increased from 8.7 Mtoe in 2004 to 21.6 Mtoe in 2018 and it is estimated that this value will increase at a diminishing rate by 2030. The results of OFANGBM(1,1) present that the energy consumption from RES in Italy will reach to 22.2 Mtoe in 2030 with the AAGR is 0.2% for the period 2018-2030 (Fig. 7b). Fig. 7c presents the share of RES in GFEC in Italy and it is estimated that this value will be 18.7% in 2020 and 20.0% in 2030. The national target of Italy on this issue is equal to 17% in 2020 (Eurostat, 2020b). Additionally, this share in 2020 is estimated as 19.2-23.3% by Cucchiella et al. (2018) and 18.9% by Simionescu et al. (2020). Therefore, result of this study is closer to Simionescu et al. (2020).

In Spain, GFEC has decreased from 97.9 Mtoe in 2004 to 89.2 Mtoe in 2018 and is forecasted as 84.5 Mtoe in 2030 (Fig. 8a). On the other hand, energy consumption from RES has increased

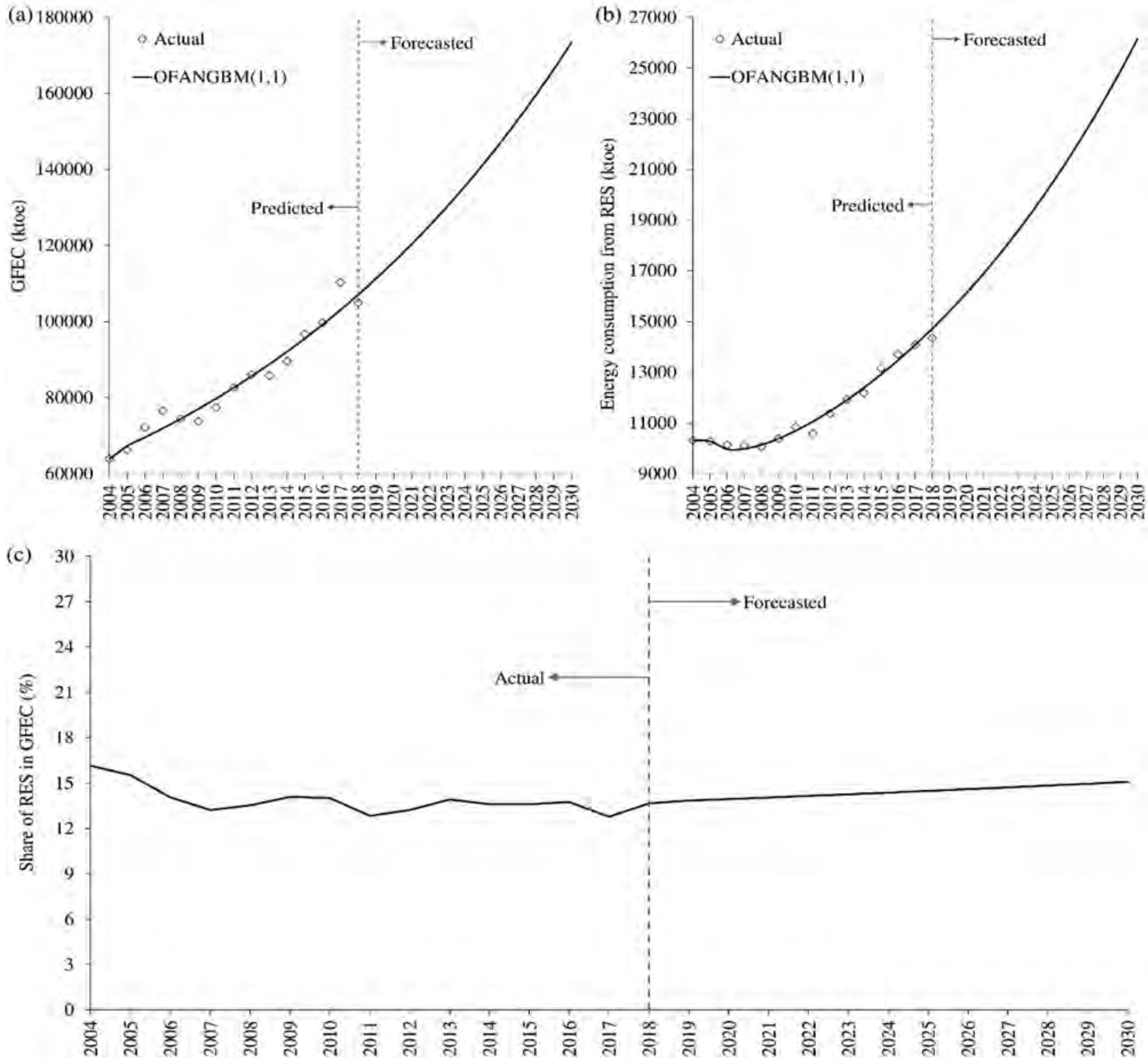

Fig 9. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in Turkey by 2030.

from 8.1 Mtoe in 2004 to 15.5 Mtoe in 2018 with the AAGR is %4.7 and it is estimated that this value will reach to 23.2 Mtoe in 2030 with the AAGR is 3.4% from 2018 to 2030 (Fig. 8b). Fig. 8c presents that the share of RES in GFEC will be 19.0% in 2020 and 27.5% in 2030 according to the results of OFANGBM(1,1). Spain has set the national target on this issue as 20% for the year 2020 (Eurostat, 2020b). Additionally, the share of RES in GFEC in 2020 is estimated as 16.8-20.0% by Cucchiella et al. (2018) and 18.8% by Simionescu et al. (2020). Therefore, it can be said that result of this study is consistent with the literature.

The prediction and forecasting results of OFANGBM(1,1) for gross final energy consumption (GFEC), energy consumption from RES and its share in Turkey are presented in Fig. 9. Turkey ranks the fifth place in GFEC among the European countries in 2018. GFEC of Turkey has increased from 63.9 Mtoe in 2004 to 105.0 Mtoe in 2018 and it is forecasted that this value will increase to 173.4 Mtoe in 2030 with the AAGR is 4.3% for the period 2018-2030. Additionally, energy consumption from RES has increased from 10.3 Mtoe in 2004 to 14.3 Mtoe in 2018 with the AAGR is %2.4. OFANGBM(1,1) presents that this value will reach to 26.1 Mtoe in 2030 with the AAGR is 5.1% from 2018 to 2030 (Fig. 9b). The share of RES in GFEC is estimated as 13.9% in 2020 and 15.07% in 2030 is presented in Fig. 9c. The national target of Turkey on the share of RES in GFEC is 20.5% for the year 2023 (ETKB, 2014). In this study, this value is estimated as 14.6% in 2023.

Fig. 10 presents the prediction and forecasting results of OFANGBM(1,1) for gross final energy consumption (GFEC), energy consumption from RES and its share in UK. GFEC has decreased from 153.8 Mtoe in 2004 to 133.7 Mtoe in 2018. It is forecasted that GFEC will decrease to 132.2 Mtoe in 2030 with the AAGR is -0.1% for the period 2018-2030 (Fig. 10a). Energy consumption from RES has increased from 1.4 Mtoe in 2004 to 14.7 Mtoe in 2018 with the AAGR is 18.3% and it is forecasted that this value will reach to 39.3 Mtoe in 2030 with the AAGR is 8.5% for the period 2018-2030 (Fig. 10b). Additionally, the share of RES in GFEC is estimated as 13.4% in 2020 and 29.7% in 2030 (Fig. 10c). The national target of UK on this issue is equal to 15% in 2020 (Eurostat, 2020b). Moreover, this share in 2020 is estimated as 11.8-13.7% by Cucchiella et al. (2018) and 9.6% by

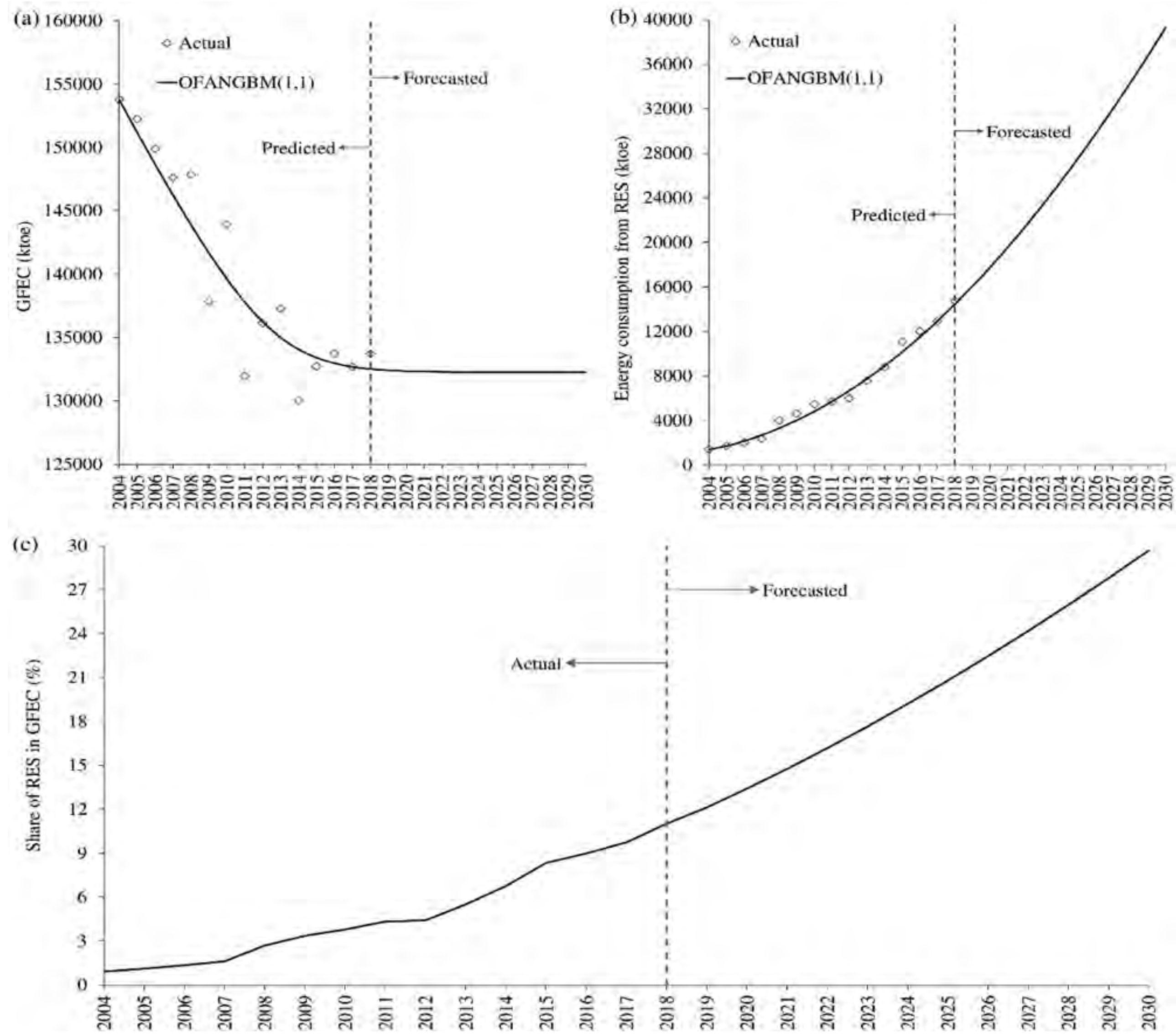

Fig 10. Forecasting results of OFANGBM(1,1) for (a) GFEC, (b) energy consumption from RES and (c) its share in UK by 2030.

Simionescu et al. (2020). Therefore, it can be said that result of this study is closer to the national target of UK for the year 2020.

Conclusions

This study presents an improved form of fractional nonlinear grey Bernoulli model (FANGBM(1,1)) which is called optimized fractional nonlinear grey Bernoulli model, briefly as OFANGBM(1,1). The main difference of OFANGBM(1,1) from FANGBM(1,1) is that the background value λ of OFANGBM(1,1) is in the range of 0-1, not equal to 0.5. To obtain optimal parameters of grey prediction models, genetic algorithm (GA) method is used. The prediction performance of two models are compared for the prediction of gross final energy consumption (GFEC) and energy consumption from renewable energy sources (RES) in France, Germany, Italy, Spain, Turkey and UK for the data of 2004-2018. By using OFANGBM(1,1), GFEC, energy consumption from RES and its share in these countries are forecasted by 2030. The following conclusions are obtained as:

- It is obtained that OFANGBM(1,1) gives higher prediction results than that of FANGBM(1,1) in all cases.
- GFEC in France, Germany, Italy, Spain, Turkey and UK for the year 2030 is estimated as 151.7 Mtoe, 227.6 Mtoe, 110.8 Mtoe, 84.5 Mtoe, 173.4 Mtoe and 132.2 Mtoe, respectively.
- Energy consumption from RES in France, Germany, Italy, Spain, Turkey and UK for the year 2030 is estimated as 28.5 Mtoe, 53.8 Mtoe, 22.2 Mtoe, 23.2 Mtoe, 26.1 Mtoe and 39.3 Mtoe, respectively.
- The share of RES in GFEC in France, Germany, Italy, Spain, Turkey and UK for the year 2030 is forecasted as 18.8%, 23.6%, 20.0%, 27.5%, 15.1% and 29.7%, respectively.
- Additionally, the national target of these countries on the share of RES in GFEC are compared with the result of this study.

Some suggestions can be outlined for further studies:

- In this study, renewable energy sources are considered in total. For the further studies, hydro, solar, wind, geothermal and biomass energy can be forecasted separately with using this model. By this way, the share of these renewable energy sources in total RES can be estimated.
- OFANGBM(1,1) can be combined with the rolling mechanism technique or machine learning models or kernel based method and results of this study can be compared with it.

- In this study, optimal parameters of OFANGBM(1,1) are obtained by genetic algorithm (GA). In further studies, optimal parameters of this model can be obtained by other algorithms. Kong and Ma (2018) compared the performance of GA with the other algorithm methods such as Particle Swarm Optimizer (PSO), Grey Wolf Optimizer (GWO) and Ant Lion Optimizer (ALO) on the nonlinear parameter optimization of NGBM(1,1). As a result, it was obtained that these algorithms have their own advantages and disadvantages.
- Prediction performance of this study are tested by mean absolute percentage error (MAPE) values. Maybe, forecasting results can be tested with expanding window method.
- On the other hand, COVID-19 outbreak has changed the energy consumption balance of the countries. In particular, energy consumption in residences has increased, as experts and politicians encourage people to stay at home (Graff and Carley, 2020). This may lead to an increase in solar PV investments in residential buildings (IRENA, 2020). In the coming years, new jobs may be created in many fields of renewable energy and new incentives may be introduced by governments for investment in the renewable energy sector. Therefore, fractional nonlinear grey Bernoulli models can be used to forecast investments in the renewable energy sector and the share of energy consumption in energy sector for the further studies.

Declaration of Competing Interest

None.

Acknowledgement

The corresponding author states that there is no conflict of interest.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.spc.2020.07.009

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