Article

How to Predict Energy Consumption in BRICS Countries?

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Abstract: Brazil, Russia, China, India, and the Republic of South Africa (BRICS) represent developing economies facing different energy and economic development challenges. The current study aims to predict energy consumption in BRICS at aggregate and disaggregate levels using the annual time series data set from 1992 to 2019 and to compare results obtained from a set of models. The time-series data are from the British Petroleum (BP-2019) Statistical Review of World Energy. The forecasting methodology bases on a novel Fractional-order Grey Model (FGM) with different order parameters. This study contributes to the literature by comparing the forecasting accuracy and the predictive ability of the FGM(1, 1) with traditional ones, like standard GM(1, 1) and ARIMA(1, 1, 1) models. Moreover, it illustrates the view of BRICS's nexus of energy consumption at aggregate and disaggregates levels using the latest available data set, which will provide a reliable and broader perspective. The Diebold-Mariano test results confirmed the equal predictive ability of FGM(1, 1) for a specific range of order parameters and the ARIMA(1, 1, 1) model and the usefulness of both approaches for energy consumption efficient forecasting.

Keywords: energy consumption; BRICS; GM (1, 1), fractional-order; GREY; forecasting accuracy

1. Introduction

Brazil, Russia, India, China, and South Africa (BRICS countries) belong to the most prominent and fastest developing economies. Although the dynamics of their growth differ across countries, they consume more and more energy. The study aims to forecast energy consumption in Brazil, China, India, Russia, and South Africa at both aggregates and disaggregate levels based on the time series observed in the years 1992–2019.

Energy plays the most crucial role in the development and achieving the sustainable economic growth of any country. The significance of energy is more critical in countries with less reserve or domestic energy sources (oil, gas, coal, hydro, etc.). BRICS is falling in the list of countries spending many energy resources to fulfill their domestic needs in residential, agricultural, and industrial requirements. The financial spending on the import of crude oil is an extra burden on the economy. Therefore, there is a need for correct forecasting about energy consumption.

In the modern era, due to globalization, the relationship among different countries are more tied up with each other in terms of social, political, and economy-wise. There is fierce competition among the developed as well as developing countries. For fulfilling the economic challenges of the 21st century, every nation is trying to achieve a sustainable level of economic growth, so countries need a sustainable supply of energy to run their economies properly. Ultimately, energy requirements lead the energy consumption in the country. However, there is vast potential to address this hot issue because massive flaws have been observed due to the traditional techniques.

The global energy consumption in 2019 amounted to 173,340 tera-watt hours, while BRICS participated in this consumption in 35.79%. Particularly China is the leading energy consumer globally, consuming up to 22.71% of the global magnitude. It can also be
observed that global energy consumption tends to decrease annually by 1–2%. However, in Brazil, China, India, and South Africa, energy consumption exhibits positive growth rates. On the other hand, Russia is reducing its energy consumption, and it follows the global decreasing trend.

When looking at the particular energy sources, the global energy consumption consisted of 30.93% oil, 25.30% coal, 22.67% natural gas, 8.00% biofuels and waste, 6.03% hydro, 4.00% nuclear, and 3.07% others in 2019. Taking into account global energy consumption structure, in the paper, the focus is put on the aggregate energy consumptions and traditional energy sources, which are to be limited over time but still play a crucial role in energy consumption and keeps particular countries far from sustainable development goals. Thus, the following disaggregates are included: oil, coal, natural gas, and hydro energy.

The paper’s novelty lies in applying the fractional-order $GM(1, 1)$ model ($FGM(1, 1)$, hereafter) proposed by [1] to forecasting energy consumption in BRICS countries at both aggregates and disaggregates levels. This is the first application of this model in the empirical analysis to the authors’ best knowledge. That is why the model needs to compare to well-known forecasting techniques based on the time series analysis, such as a standard grey model $GM(1, 1)$ proposed by [2] and Auto Regressive, Integrated, Moving Average ($ARIMA(1, 1, 1)$), which was initially proposed by [3]. The model comparison is two-fold. In the first step, standard measures of forecasting accuracy such as mean square error ($MSE$) and mean absolute percentage error ($MAPE$). In contrast, in the second one, the models are compared for equal forecasting ability using the Diebold-Mariano test [4].

The rest of the paper has organized as follows. Section 1.1 provides an energy profile of BRICS countries, and Section 1.2 reports the relevant literature review. Section 2 provides materials and methods. Section 3 presents the empirical results. Section 4 provides the discussion of results. The final Section 5 concludes the paper and discusses policy implications.

### 1.1. Energy Profile of BRICS Countries

In this Section, we briefly present the energy profile of BRICS. There is enormous potential in the energy sector of BRICS. The facts and figures of the following energy for BRICS have been taken from the BRICS energy report, 2020.

Brazil generated 306.8 million tons of oil equivalent (mtoe) of primary energy in 2018, with 14 mtoe of unutilized energy and natural gas reinjection (in 2019: 327 and 17 mtoe, respectively). Production of oil surpassed demand by 52.5%, accounting for most of the Brazilian surplus (in 2019: 64%).

After China and the United States (US), Russia is the world’s third-largest producer and user of energy resources, accounting for 10% of global production and 5% of global consumption. The Russian energy complex, which includes the oil, gas, coal, electricity, and heat supply industries, is a significant source of revenue for the Russian Federation’s budget.

After the US and China, India is the world’s third-largest energy user, producing around 6% of global demand. Between 2010 and 2019, the country’s energy consumption increased by 50%. At the same period, coal accounts for 56% of global primary energy output. India produces just over half of its oil. The level and structure of energy production have changed significantly between 2010 and 2019: the volume of energy production has increased by 40%. The share of conventional biomass replaced by coal in the energy mix has decreased significantly.

China’s energy output grew steadily in 2018, reaching 3.77 billion tons of coal equivalent, up 5.0 percent year on year and the highest amount in the last six years, accounting for 18.7% of global production. In 2018, fossil fuels accounted for 81.8 percent of China’s energy output, with coal accounting for 69.1% and non-fossil accounting for 18.2%. China has surpassed the US as the world’s largest hydropower, wind power, and solar power installed capacity nation. China’s overall energy consumption in 2018 was 4.64 billion tons of coal equivalent, up 3.3 percent year on year. China’s low rate of energy consumption growth helps to sustain the country’s medium-high-speed economic growth.
The Republic of South Africa (RSA) is the continent’s second-largest energy user. South Africa’s total primary energy consumption in 2019 was 135 mtoe, down 5.6 percent from 2010. Coal dominates the energy demand structure, accounting for about 75% of total consumption. South Africa is a net energy exporter, exporting more than 45 mtoe of coal to global markets each year, while having minimal domestic oil and natural gas output and relying on imports for most of these fuels. The structure of energy production has remained nearly unchanged since 2010, but overall production has decreased slightly.

1.2. Literature Review

Many studies explore energy-related issues, but most studies focused on the causal relationship between energy consumption and economic growth using univariate or multivariate analysis. The previous studies found inconsistent results. We can categorize the results of earlier investigations into four different groups. (1) Many studies found bidirectional causality, including [5] for Korea. (2) Some studies found unidirectional causality while estimating electricity consumption to GDP. The studies of [6] for Turkey; [7] for Taiwan; [8] for Turkey, France, Germany, and Japan found strong evidence of unidirectional causality. (3) Some authors found evidence of unidirectional causality estimating results from economic growth to electricity consumption; [9] for New Zealand and Australia; [10] for Sweden. (4) The last group of studies found no evidence of causality between electricity consumption and economic growth [11]. The above examples show a strong need for energy consumption forecasting and linking it to economic growth and an energetic sustainable policy in the future.

There is a large plethora of literature available on the issue of energy consumption forecasting. Many studies used ARIMA methods for forecasting energy consumption, e.g., [12–22], and some studies were forecasted by comparing the ARIMA approach with some other methods. On the other hand, some studies used the grey methods for energy consumption forecasting. Referring only to the BRICS group of countries, there is numerous literature on energy consumption in China. Besides, Brazil and India are sometimes represented; however, Russia and South Africa are rarely the analysis subjects.

In past research, [17] investigated energy demand in the transport sector using ARIMA, exponential smoothing, and multi-regression models. On the other hand, the study of [19] forecasted China’s primary energy consumption by comparing the ARIMA and grey models. In [20], the authors estimated electricity consumption for Brazil by applying the Spatial ARIMA model. There are very few studies that evaluated energy consumption for BRICS by using the ARIMA model. Some studies forecasted energy consumption using the ARIMA forecasting method like [12–17,19] for China, [20] for Brazil, and [22] for South Africa. On the other hand, some studies used the grey Markov method with rolling mechanism and singular spectrum analysis for energy consumption forecasting like [23] for India. Similarly countrywide studies are [19,24–81] for China; [15] for the US; [82] for China and India; [83] for BRICS; [84] for China and US, [85,86] for Brazil, and [87] for Asian countries.

The grey forecasting method proposed by [2] has gained popularity among researchers because it is efficient in a small number of observations [17]. Similarly, the grey method is suitable to tackle forecasting in the case of inaccuracy of data. There are numerous applications of grey models; many of them are related to energy consumption.

In [21], the authors analyzed several versions of grey models (e.g., grey model including GM(1,1); GM(1, n); Rolling GM(1,1) Rolling GM(1, 1, Xn) and Rolling NOGMN(1, 1), and forecasted electricity consumption from 2015 to 2020. The study [32] analyzed electricity consumption for China using the continuous fractional-order grey model and forecasted from 2010 to 2014. In [34], authors analyzed grey GM(1, 1), Gross weight grey model, and GVGM(1, 1) for China and forecasted from 2010 to 2020. In [35], authors analyzed energy consumption for China using the improved hybrid grey model (INHGM-Markov) and forecast from 2018 to 2022.
Some researchers developed the model’s extended versions using the standard $GM(1,1)$ grey forecasting model, as [25] proposed an improved version of the seasonal rolling grey prediction model to estimate the accurate forecasting for traffic flow problems. Moreover, [26] proposed fractional-order accumulation techniques and forecasted from 1999 to 2007 for China and from 1999 to 2008 for the US. [27] developed a new time-delayed polynomial grey model, which has shown outstanding results when forecasting China’s natural gas consumption and forecasted from 2005 to 2013 and 2014 to 2020. [28] predicted China’s energy consumption by incorporating genetic programming in the grey prediction approach and forecasted from 2004 to 2007. Similarly, [29] developed a generalized fractional-order grey model using the fractional calculus and forecasted it from 2010 to 2014. [46] forecast coal stockpiles for China using grey spontaneous combustion forecasting models and forecasted from day 11 to 20. [47] analyze the electricity consumption for China using grey prediction with the nonlinear optimization method and forecasted from 2014 to 2020. [48] examined electricity consumption using grey $GM(1,1)$ and combined improved grey ($DCOGM(1,1)$) prediction models and forecasted from 2017 to 2021. The results show that $DCOGM(1,1)$ shows better results than the traditional grey $GM(1,1)$ model. [49] analyzed electricity consumption for China using the grey polynomial prediction model and forecasted from 2011 to 2015. [50] analyzed the energy vehicle industry for China using grouping approach-based nonlinear grey Bernoulli model (DGA-based NGBM $(1,1)$) and $GM(1,1)$ forecasting from 2018Q1 to 2020Q4. [57] forecast for by using Self-adaptive intelligence grey predictive model and forecasted for 2014. The results indicate that the Self-adaptive grey model shows better results than $GM(1,1)$ and discrete grey ($DGM(1,1)$) models. The study [87] used a hybrid dynamic grey model for forecasting electricity consumption for China and the US.

2. Materials and Methods

This Section is divided into three Sections related to data sources description, forecasting models, and forecasting accuracy.

2.1. Data Sources and Descriptive Statistics

The present study is based on the secondary data source consisting of annual observations on the BRICS economy for 1992–2019. The starting date is limited by the case of Russia being founded in 1991 after the dissolution of the Soviet Union. The current study uses the energy consumption in BRICS and for empirical analysis. The data on energy consumption (EC) at aggregate and disaggregate energy consumption components (oil, gas, coal, and hydroelectric) are taken from British Petroleum (BP-2019) Statistical Review of World Energy. All variables are measured in a million tons of oil equivalent (mtoe) units, and the description of variables is as: (1) Aggregate energy consumption (agg); (2) Oil consumption (oil); (3) Gas consumption (gas); (4) Coal consumption (coal); (5) Hydroelectric consumption (hydro).

To begin the analysis, the time series are presented in Figure A1 in the Appendix A. One can notice that in most cases, energy consumption was growing over time. Only in Russia, a decreasing trend is observed in coal energy consumption. Total (aggregate) energy consumption was decreasing in 1992–1998. Oil and gas consumption decreased in 1992–1996; since that time, a growing tendency has been observed.

The descriptive statistics of the selected aggregate and disaggregate energy consumption series of BRICS are provided in Table A1 in the Appendix A. The mean value of “agg” ranges from 111.4 (mtoe) in South Africa to 1909.42 (mtoe) in China, in BRICS countries. However, the mean value of “coal” ranges from 13.71 in Brazil to 1298.20 in China. Similarly, the average “gas” is lowest in South Africa with 2.42, while it is highest in Russia with 346.38. On the other hand, average “hydro” is lowest in South Africa with 0.30 and highest in China with 123.78. Finally, average “oil” is lowest in South Africa with 24.55, while it is highest in China with 360.67 mtoe.
As far as variability, measured by the standard deviation, is concerned, the BRICS countries are pretty diversified, according to different energy sources. South Africa has the smallest value (13.51 mtoe), while China has the highest value (919.14 mtoe) for aggregate energy consumption. China exhibits maximum variability for aggregate and disaggregates time series (coal, gas, oil, and hydro). The variability coefficients expressed as standard deviation/mean ratio, amounted from 42.9% for “coal” to 94.7% for “gas”. It is related to the highest energetic expansion of the Chinese economy over the last four decades. India shows the second-highest variability coefficients. The amount from 23.8% for oil to 42.4% for gas. Russia exhibits the most negligible variability (from 4.8% for hydro to 16.9% for oil).

The study testing for normality using Jarque and Bera test [88] indicates that most of the time series satisfied the normal distribution. Only aggregate energy consumption and coal energy consumption in Russia do not fulfill this condition. The departures from normality do not deteriorate the results. In the case of FGM(1,1), a normal distribution is not assumed. It is necessary for estimating the ARIMA(1,1,1) parameters. However, when the number of observations is relatively tiny (T = 28), such deviations are admissible.

The unit root characteristics of the time series are presented in Table A2. Most cases confirmed the unit root hypothesis apart from four series, i.e., Russia’s “agg”, “coal” and “hydro” energy, and South Africa’s “hydro” energy, which were stationary. In the case of China’s “gas” and “oil” the order of integration was bigger than one. In these cases, ARIMA(1,1,1) was not applicable.

2.2. Methodology

The current study is based on FGM(1,1) grey model. The model was introduced to the literature in 2019. Its application to energy consumption forecasting is still not recognized by the authors of the paper [1] based on simulation results. In the current study, the FGM(1,1) model is compared to a standard GM(1,1) model, as well as the ARIMA (p,d,q) widely recognized in the forecasting literature. We focus on model comparison in terms of forecasting ability.

2.2.1. Unit Root Testing and ARIMA (p,d,q) Model

The most recognized representation for nonstationary time series is the ARIMA model that can be written in the form:

$$\varnothing(L)(1 - L)^d(Y_t - \mu_t) = \theta(L)\varepsilon_t$$  \hspace{1cm} (1)

where \(\varnothing(L)\) and \(\theta(L)\) are polynomials in the lag operator, \(L\) defined such that \(L^nx_t = x_{t-n}\), \(\mu_t\) is the unconditional mean, \(d\) is the order of integer differencing, and \(\varepsilon_t\) is a white noise process (i.i.d. normally distributed) (for further details, see [3,89]). This model is termed an ARIMA\((p,d,q)\) to indicate \(p\) lags in the AR and \(q\) lags in the MA terms, and \(d\) an integer differencing. To estimate the parameters of the ARIMA model, the maximum likelihood method is recommended. The model selection procedure, related to lag parameters \(p\) and \(q\), is based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC) [90]. ARIMA model refers to integrated time series, which become stationary after \(d\)-th times differencing. To determine whether a time series is stationary or not, the Augmented Dickey and Fuller test is typically used [91].

2.2.2. Fractional-Order GM (1, 1) Model

The construction of the fractional-order GM(1,1) grey model methodology is explained by [1]. As it is quite a new approach, it is presented in this Section.

**Definition 1.** The sequence of raw data series is \(X^{(0)} = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\), where \(r \in \mathbb{R}^+\), which is known as \(X^{(r)} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n))\) is the \(r\) th-order accumulating sequence of \(X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))\) [55] where \(\Gamma(n)\) is denoting the gamma function,
The general idea of Diebold-Mariano’s test relies on two-time series, including actual hypothesis to be tested says that the alternative methods are equally accurate on average. 

By values and forecasts of a predicted variable, say \( GM \) is representing the direct \( GM \) is representing the

\[
\text{errors. There are plenty of such measures, such as MSE and MAPE (See, [93] (p. 309).}
\]

\[
\text{their comparison based on the mean square error was selected for comparison because the differences between forecast errors were relatively low. It is worth emphasizing that such a compar-
}\]

\[
x^{(r)}(k) = \sum_{i=1}^{k} \frac{\Gamma(r + k - i)}{\Gamma(k - i + 1) \Gamma(r)} x^{(0)}(i), k = 1, 2, \ldots, n
\]

\[
\text{Definition 2. Assume that } X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \text{ is the sequence of raw data, where } r \in R^+, \text{ which is known as } X^{(r)} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)) \text{ is the rth order reducing generation sequence of } X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \text{ [55].
}\]

\[
x^{(-r)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r + 1)}{\Gamma(i + 1) \Gamma(r - i + 1)} x^{(0)}(k - i)
\]

\[
\text{Definition 3. Assume that } X^{(r)} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)) \text{ is defined as Definition 1, and } X^{(-r)} = (x^{(-r)}(1), x^{(-r)}(2), \ldots, x^{(-r)}(n)) \text{ is followed the Definition 2.}
\]

\[
\text{Thus, } Z^{(-r)} = (z^{(-r)}(2), z^{(-r)}(3), \ldots, z^{(-r)}(n)), \text{ where
}\]

\[
Z^{(r)}(k) = \frac{x^{(r)}(k) + x^{(r)}(k - 1)}{2}, k = 2, 3, 4, \ldots, n,
\]

The model formula

\[
x^{(r-1)}(k) + az^{(r)}(k) = b
\]

is representing the FGM(1,1). The FGM(1,1) introduced a fractional-order \( r \), which can take non-integer values. The following conditions are distinguished: if \( r = 1 \), Equation (5) is representing the GM(1,1)

\[
x^{(0)}(k) + az^{(1)}(k) = b,
\]

Which is called as standard grey GM(1,1) model described in [2] if \( r = 0 \), Equation (5) is representing the direct GM(1,1) modeling.

\[
x^{(-1)}(k) + az^{(0)}(k) = b
\]

It is expected that the development coefficient \( a \) to be negative and the intension parameter \( b \) to be positive (See, [92] chapter 7, p. 149).

2.2.3. Forecasting Accuracy Measures

The most popular measures of forecast accuracy concentrate on computing forecast errors. There are plenty of such measures, such as MSE and MAPE (See, [93] (p. 309). Their usefulness consists of showing the differences in accuracy of computed forecasts but say nothing about the method of forecasting.

In 1995, ref. [4] derived a testing procedure of equal predictive accuracy. The hypothesis to be tested says that the alternative methods are equally accurate on average. The general idea of Diebold-Mariano’s test relies on two-time series, including actual values and forecasts of a predicted variable, say \( y_t \) and \( \hat{y}_t \), as well as on the loss function depending on the forecast and actual values only through the forecast error, defined as: 

\[
g(y_t, \hat{y}_t) = g(\hat{y}_t - y_t) = g(e_t).
\]

The loss function may take many different forms, which is discussed further in this part. What we compare is a loss differential between the two forecasts, coming from two competing models of the form: 

\[
d(t) = g(e_1) - g(e_2).
\]

The forecasting methods are equally accurate if \( E(d(t)) = 0 \), which is assumed under the null hypothesis.

This paper applied the Diebold-Mariano test to compare a standard GM(1,1) model, ARIMA(1,1,1), and FGM(1,1) model estimated for different \( r \) values. The loss function based on the mean square error was selected for comparison because the differences between forecast errors were relatively low. It is worth emphasizing that such a compar-
ison is possible only if a sufficient number of observations are necessary to estimate the ARIMA model.

3. Results

The results of forecasting energy consumption using the $FGM(1,1)$ model are presented in Table 1 for aggregate energy consumption and in Tables A3–A6 for disaggregates energy consumption. All results of aggregate and disaggregate energy consumption is reported with the following values: MAPE, MSE, development coefficient ($a$), and grey input ($b$). In the $FGM(1,1)$, different ($r$) values are applied. In the study, $r = \{-1.5; -0.9; -0.5; -0.1; -0.05; 0; 0.01; 0.05; 0.1; 0.5; 0.9; 1; 1.5\}$.

In Table 1, the results of aggregate energy consumption are reported. The minimum MAPE values were taken as the main criterion of model selection. Additionally, the assumptions for $a < 0$ and $b > 0$ were to be fulfilled. For Brazil, the order ($r$) is $r = 0.9$ with the minimum MAPE= 3.43; for China, the order ($r$) is $r = 0.5$ with the minimum MAPE= 10.030; for India, the order ($r$) is $r=1$ with the minimum MAPE = 2.163, and for Russia, the order ($r$) is $r = 1$ with the minimum MAPE = 3.632. Finally, South Africa has the least MAPE = 21.565 with the parameters $a = -0.001$, and $b = 1.376$, where the value of $r = 0$.

In Table A4, the results of gas consumption are reported. For Brazil, the order ($r$) is $r=0.1$ with the minimum MAPE = 22.262 with the appropriate sign of grey parameters. For China, the order ($r$) is $r=1$ with the minimum MAPE = 18.884; for India, the order ($r$) is $r = 0.1$ with the minimum MAPE =7.842, and for Russia, the order ($r$) is $r = 1$ with the minimum MAPE = 3.408. For South Africa, the best model is for the value of $r = 0.9$. It has the least MAPE = 30.042.

In Table A5, the results of coal consumption are reported. For Brazil, the order ($r$) is $r = 1$ with the minimum MAPE = 8.040, for China, the order ($r$) is $r = 0.5$ with the minimum MAPE = 13.971, for India, the order ($r$) is $r=1$ with the minimum MAPE = 4.489, and for Russia, the order ($r$) is $r = 1.5$ with the minimum MAPE = 12.986. South Africa has the least MAPE = 3.335, where the value of $r = 0.9$.

Finally, in Table A6, the results of hydro energy consumption are reported. For Brazil, the order ($r$) is $r = 0.9$ with the minimum MAPE = 5.552. For China, the order ($r$) is $r=1$ with the minimum MAPE = 11.418, for India, the order ($r$) is $r = 1$ with the minimum MAPE = 8.642, for Russia, the order ($r$) is $r = 1.5$ with the minimum MAPE = 14.648, and for South Africa, the order ($r$) is $r = 1.5$ with the least MAPE = 122.067.

Summing up, the most frequently $FGM(1,1)$ model with $r = 0.9$ and $r = 1$ were supported by the data. Quite often, the following values: $r = 1.5$ and $r = 0.1$ were indicated. Moreover, $r = 0.5$ was shown twice and $r = 0$ once. It means that the $FGM(1,1)$ model outperformed the $GM(1,1)$ in terms of energy consumption prediction since it allows more flexible fitting to the time series’ actual values. As $r = 1$ corresponds to the $GM(1,1)$, one can notice that this model is quite valuable for energy consumption prediction.

As mentioned in Section 2.2.3, the results of forecasting can be compared, and the models’ effectiveness in prediction can be evaluated using the Diebold-Mariano test. The results of the model comparison are presented in Table 2.
### Table 1. Mean absolute percentage error (MAPE) and Mean Square Error (MSE) for Aggregate Energy Consumption of BRICS in 1992–2019.

| Country | MAPE | MSE |
|---------|------|-----|
| Brazil  | 3.437 3.467 3.843 4.299 5.652 3.430 3.887 15.476 | 3.464 3.894 5.659 4.182 5.294 114.571 | 1.689 |
| China   | 3.065 2.463 3.199 2.916 3.502 3.032 3.199 | 2.163 10.946 3.921 4.676 11.662 | 21.565 |
| India   | 2.463 2.463 2.916 3.032 3.199 2.163 3.921 | 2.163 10.946 3.921 4.676 11.662 | 21.565 |
| Russia  | 2.463 2.463 2.916 3.032 3.199 2.163 3.921 | 2.163 10.946 3.921 4.676 11.662 | 21.565 |

For Brazil, the order \( r = 0.9 \) with the minimum MAPE = 3.437 and MSE = 15.476 with the appropriate sign of grey parameters. For China, the order \( r = 0.9 \) with the minimum MAPE = 3.065 and MSE = 15.476 with the appropriate sign of grey parameters. For India, the order \( r = 0.9 \) with the minimum MAPE = 2.463 and MSE = 15.476 with the appropriate sign of grey parameters. For Russia, the order \( r = 0.9 \) with the minimum MAPE = 2.463 and MSE = 15.476 with the appropriate sign of grey parameters.

**Note:** MSE = Mean Standard Error; MAPE = Mean Absolute Percentage Error. The shaded area indicates the best model for a given country. In Table A3, the results of oil consumption are reported. For Brazil, the order \( r = 0.9 \) with the minimum MAPE = 3.437 and MSE = 15.476 with the appropriate sign of grey parameters. For China, the order \( r = 0.9 \) with the minimum MAPE = 3.065 and MSE = 15.476 with the appropriate sign of grey parameters. For India, the order \( r = 0.9 \) with the minimum MAPE = 2.463 and MSE = 15.476 with the appropriate sign of grey parameters. For Russia, the order \( r = 0.9 \) with the minimum MAPE = 2.463 and MSE = 15.476 with the appropriate sign of grey parameters.
| GM(1,1)  | Brazil | Oil | Gas | Coal | Hydro | FGM(1,1)  | Agg | Oil | Gas | Coal | Hydro | Agg | Oil | Gas | Coal | Hydro | Agg | Oil | Gas | Coal | Hydro |
|---------|--------|-----|-----|------|-------|------------|-----|-----|-----|------|-------|-----|-----|-----|------|-------|-----|-----|-----|------|-------|-----|-----|-----|------|-------|
| r = 0   | >0.1   | >0.1| >0.1| >0.1 | >0.1   | 0.044      | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.01| >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.05| >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.9 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 1.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.01| >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.05| >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 0.9 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| r = 1.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1| >0.1 | >0.1   |
| ARIMA   | 0.020  | 0.022| 0.024| 0.021| 0.016 | 0.019      | 0.048| 0.040| 0.027| 0.038 | 0.024 | 0.026| 0.015| 0.015| 0.015| 0.024 | 0.023| 0.029| 0.039| 0.020| 0.000 |
| r = 0.01| >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | NA | NA | >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1 | >0.1   | >0.1 | >0.1| >0.1| >0.1 | NA     |
| r = 0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | NA | NA | >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1 | >0.1   | >0.1 | >0.1| >0.1| >0.1 | NA     |
| r = 0.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | NA | NA | >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1 | >0.1   | >0.1 | >0.1| >0.1| >0.1 | NA     |
| r = 1.5 | >0.1   | >0.1| >0.1| >0.1 | >0.1   | >0.1       | NA | NA | >0.1| >0.1 | >0.1   | >0.1| >0.1| >0.1 | >0.1 | >0.1   | >0.1 | >0.1| >0.1| >0.1 | NA     |

**Note:** Rejecting the null hypothesis is highlighted with the shaded area; agg = aggregate.
The conclusion of model comparison using the Diebold-Mariano test is that the \( FGM(1,1) \) for many values of \( r \), \( GM(1,1) \), and \( ARIMA(1,1,1) \) possess an equal predictive ability for energy consumption forecasting in BRICS countries. This is a universal conclusion, since if the observation number is large, one can rely on both the stochastic time series model like ARIMA and grey type models. As concerns \( FGM(1,1) \), for small negative \( r \) values like \(-1.5\), the results are much worse. This conclusion is useful because one can limit the range of possible \( r \) values between \((-1.00; +1.00)\). The two results (China, hydro \( r = 0.00 \) and India coal, \( r = -0.05 \)) when the null hypothesis of equal predictive ability was rejected, can be considered random.

4. Discussion

BRICS countries belong to the developing economies group, although China has become a global competitor in some areas [94]. Developing countries desire precise forecasts of both scales of growth and energy consumption. They also need to optimize energy exploitation from different sources and adopt new technologies for renewable energy sources. As the economy grows, energy consumption increases as well. It is a danger in increasing energy consumption over a very long time. According to the law of entropy, the resources are limited, and too much recycling will result in energy waste [95]. Proponents of ecological economics consider the problem of sustainability to be that of sustainable macroeconomic scale, acknowledging the possibility that the economy may become or may already be so large that it places demands on the environment exceeding its carrying capacity [96].

However, there are strict limitations to energy consumption. They divide into global and country-specific limitations. Global recommendations origin is in the United Nations’ 2030 Agenda for the Sustainable Development Goals (SDGs), which all 193 UN member states accepted. Among 17 SDGs, goal 7 assumes access to affordable, reliable, sustainable, and modern energy for all, and goal 13 covers urgent action to combat climate change and its impacts. Country-specific limitations consist of natural resource exploitation, technology for energy production, and transformation and consciousness of the necessity of rationalization. Considering the above, the energy policy of BRICS countries needs continuous monitoring for forecasting accuracy and its structure according to the SDGs requirements. The most important policy recommendation is to shift energy consumption from fossil fuels (oil, gas, coal, oil shales, etc.) to renewable energy consumption. The less usage of fossil fuel will be more beneficial for the environment by providing environmental awareness.

The results of the grey and \( ARIMA \) models’ comparison presented in the current paper revealed as follows:

1. Fractional Grey Model \( FGM(1,1) \) allows a broad spectrum of parameters that adjust to the empirical data. An FGM-based approach is more comprehensive than the standard \( GM(1,1) \) model, which is “a special case” of \( FGM(1,1) \) for \( r = 1 \).
2. According to the Diebold-Mariano test results, the estimated \( FGM(1,1) \) models taking parameters’ range \((-1; 1)\) confirmed equal predictive ability with \( GM(1,1) \) model as well as \( ARIMA(1,1,1) \) model.
3. Although grey-type models are mostly recommended for short time series, their predictive ability is equal to \( ARIMA \) models designed for long time series. However, taking values of MSE and MAPE in empirical study, \( ARIMA(1,1,1) \) model highly outperformed \( FGM(1,1) \) in 19 cases on 25. In six cases, \( ARIMA(1,1,1) \) were not applicable. For Chinese oil and gas consumption, the time series was integrated of higher order than one. The remaining four series were stationary.
4. For some parameter “\( r \)” values, empirical \( FGM(1,1) \) models do not satisfy the grey model assumption, i.e., \( a < 0 \) and \( b > 0 \). In such circumstances, it is recommended to estimate the model for another “\( r \)” parameter value.
5. Grey-type models are helpful for forecasting in the case when only a few observations are available. Still, for long and nonstationary time series, standard time series models perform better.
In the paper [97], the authors provided a methodological comparison of probability models, fuzzy math, grey systems, and rough sets. It appears that grey models are evidently preferred in the case of small samples and incomplete information sets. They concentrate on the law of reality. On the other hand, stochastic models, such as ARIMA are designed for large samples and follow historical law. The general conclusion that both types of models possess equal predictive ability indicated by the Diebold-Mariano test allows selecting the proper procedure for given data set and forecasting perspective. The exact values of MAPE and MSE are less informative because they are valid only for a given sample. Therefore, the presented results are in line with both theory and expectations.

5. Conclusions

The BRICS are emerging economies concerning the production and management of resources and require a consistent supply of having energy resources. The BRICS countries should monitor energy consumption, focusing on the supply-demand gap of energy and its components and facilities provided to local and foreign investors. Therefore, forecasting is quite significant for energetic policy projection. Accurate forecasts of energy consumption are vital when demand grows faster. On the other hand, BRICS’s energy consumption values can be offered as fluctuating and increasing.

This study aimed to predict energy consumption in BRICS. Firstly, this paper focused on forecasting the annual energy consumption for BRICS using two types of models. It compared ARIMA, and FGM(1, 1) models by estimating the errors (MAPE) and (MSE) in the years 1992–2019. Secondly, the results have revealed that ARIMA(1, 1, 1) outperformed FGM(1, 1) when in-sample estimating errors are compared. Thirdly, model comparison using the Diebold-Mariano test confirmed the equal predictive ability of ARIMA(1, 1, 1) and FGM(1, 1) unless the FGM parameter ranges (−1, 1). The results allow concluding that if the number of observations is large enough, stochastic models such as ARIMA and grey models such as FGM are helpful for energy consumption forecasting. The procedure enabled narrowing the range of possible parameter values for r in the Fractional GM(1, 1).

Moreover, the empirical findings allow formulating some recommendations. BRICS countries need to follow SDGs concerning energetic policy keeping their economic growth level increasing. It implies a gradual structural change from traditional towards renewable energy sources. A structural change always means a significant limitation of the number of observations; therefore, the FGM(1, 1) model is recommended for predicting energy consumption in aggregate and disaggregate levels.

Author Contributions: Conceptualization, A.M.K., and M.O.; methodology, A.M.K. and M.O.; software, A.M.K. and M.O.; validation, M.O.; formal analysis, A.M.K.; investigation, A.M.K.; resources, A.M.K.; data curation, A.M.K.; writing—original draft preparation, A.M.K., and M.O.; writing—review and editing, A.M.K., and M.O.; visualization, A.M.K., and M.O. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Acknowledgments: We would like to thank Wei Meng for providing the code for Fractional-order GM (1, 1) method and for valuable guidance.

Conflicts of Interest: The authors declare no conflict of interest.
### Table A1. Summary statistics of energy consumption for BRICS in 1992–2019.

| Variable | Brazil | Russia | India | China | South Africa |
|----------|--------|--------|-------|-------|--------------|
|          | Oil    | Gas    | Coal  | Hydro | Oil          | Gas    | Coal  | Hydro | Oil    | Gas    | Coal  | Hydro | Oil | Gas | Coal  | Hydro |
| Mean     | 224.48 | 97.12  | 17.87 | 13.72 | 75.63        | 668.91 | 146.39 | 346.38 | 102.32 | 39.16  | 249.51 | 23.24 | 1099.42 | 360.69 | 81.16  | 1298.20 | 123.78 | 111.94 | 24.55 | 2.42 | 81.39 | 0.30 |
| Med      | 214.21 | 91.52  | 17.54 | 13.00 | 78.15        | 670.93 | 137.99 | 352.03 | 99.16  | 39.55  | 405.72 | 129.09 | 813.50  | 1892.64 | 346.59 | 1899.66 | 95.99  | 115.44 | 25.47 | 2.91 | 82.57 | 0.26 |
| Max      | 296.25 | 129.59 | 36.92 | 17.62 | 95.44        | 819.31 | 238.82 | 390.80 | 156.98 | 42.10  | 813.50 | 244.53 | 51.84   | 3384.43 | 666.52 | 264.26  | 1969.07 | 129.00 | 28.62  | 3.91 | 0.68 | 93.82 | 0.68 |
| Min      | 139.15 | 64.37  | 3.19  | 10.68 | 53.34        | 598.74 | 125.21 | 297.00 | 83.93  | 36.20  | 218.18 | 63.79  | 12.41   | 758.40  | 134.64 | 578.80  | 31.21  | 88.12  | 17.92 | 0.80 | 66.35 | 0.03 |
| S. D.    | 52.31  | 18.04  | 11.20 | 2.09  | 11.44        | 48.43  | 24.75  | 24.91  | 16.69  | 1.89   | 188.65 | 53.38   | 13.40   | 519.14  | 167.76 | 76.87   | 1389.66 | 95.99  | 111.94 | 24.55 | 1.25 | 8.99   | 0.17 |
| SKE      | 0.04   | 0.05   | 0.19  | 0.46  | −0.27        | 1.05   | −0.26  | −1.75  | −0.08  | 0.47   | 0.39   | 0.12    | 0.16    | 0.30    | −0.05  | −0.33   | −0.14  | −0.19  | 0.98 |
| Kurt     | 1.61   | 2.07   | 1.66  | 2.09  | 4.77         | 2.01   | 5.97   | 1.71   | 1.90   | 2.15   | 1.57   | 1.83    | 1.72    | 1.77    | 2.73   | 1.24    | 1.78   | 1.63   | 3.21 |
| J-B      | 2.25   | 1.03   | 2.28  | 2.19  | 1.29         | 8.78   | 58.27  | 1.45   | 24.65  | 1.98   | 2.44   | 1.53    | 2.45    | 2.91    | 2.96   | 2.16    | 4.59   | 3.62   | 3.09 |
| Prob     | 0.32   | 0.61   | 0.32  | 0.33  | 0.52         | 0.01   | 0.00   | 0.37   | 0.29   | 0.46   | 0.29   | 0.23    | 0.36    | 0.23    | 0.34   | 0.10    | 0.16   | 0.26   | 0.29 |
| Obs.     | 28     | 28     | 28    | 28    | 28           | 28     | 28     | 28     | 28     | 28     | 28     | 28      | 28      | 28      | 28     | 28      | 28     | 28     | 28 |

**Note:** Med: Median; Max = Maximum; Min=Minimum; S.D. = Standard deviation; Ske = Skewness; Kurt = Kurtosis; J-B = Jarque-Berra; Prob = Probability; Obs = Observations.

### Table A2. Unit Root (ADF) Testing for BRICS in 1992–2019.

| Variable | Brazil | Russia | India | China | South Africa |
|----------|--------|--------|-------|-------|--------------|
|          | Oil    | Gas    | Coal  | Hydro | Oil          | Gas    | Coal  | Hydro | Oil    | Gas    | Coal  | Hydro | Oil | Gas | Coal  | Hydro |
| Level    | −0.992 | 0.101  | −0.738 | −1.575 | −0.982        | −3.761 | −2.499 | −0.059 | −3.421 | −3.403 | −0.822 | 2.436 | −0.801 | 2.449 | −0.598 | 0.227 | 2.137 | 5.208 | −0.001 | 1.051 | −2.120 | −0.539 | −1.513 | −3.760 |
| Prob.    | 0.741  | 0.858  | 0.826  | 0.801  | 0.535         | 0.009  | 0.127  | 0.785  | 0.020  | 0.020  | 0.355  | 0.000  | 1.000  | 0.855  | 0.909  | 1.000  | 1.000  | 0.801  | 0.999  | 0.223  | 0.326  | 0.869  | 0.512  | 0.009  |
| First differ. | −4.052 | 4.136  | −3.536 | −5.597 | −4.766        | −2.786 | −4.239 | −4.965 | −3.707 | −5.383 | −0.050 | −2.313 | −3.653 | −3.735 | −5.749 | −2.202 | −4.472 | 0.605  | −2.566 | −6.424 | −3.930 | −5.038 | −4.465 |
| Prob.    | 0.005  | 0.004  | 0.007  | 0.001  | 0.001         | 0.026  | 0.005  | 0.001  | 0.000  | 0.000  | 0.000  | 0.010  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  |

**Note:** * indicate the rejection of the null hypothesis of a unit root at the 1% significant levels, respectively; agg = aggregate. ADF test with intercept.
Figure A1. Graphical trends of energy consumption for BRICS in 1992–2019.
| Country | $r = 0$ | $r = 0.01$ | $r = 0.05$ | $r = 0.1$ | $r = 0.5$ | $r = 0.9$ | $r = 1$ | $r = 1.5$ | $r = -0.01$ | $r = -0.05$ | $r = -0.1$ | $r = -0.5$ | $r = -0.9$ |
|---------|---------|------------|------------|-----------|-----------|-----------|---------|-----------|------------|------------|------------|------------|-----------|
| MSE     | 49.603  | 49.366     | 115.761    | 52.035    | 61.483    | 42.264    | 47.209  | 554.869   | 50.008     | 54.215     | 66.398     | 55.720     | 57.320    |
| MAPE    | 3.866   | 3.716      | 3.198      | 2.795     | 3.745      | 4.356      | 5.995   | 14.754    | 4.025      | 3.894      | 6.633      | 80.335     | 90.676    |
| b       | 6.992   | 7.501      | 9.428      | 11.640    | 29.519     | 60.981     | 73.023  | 181.164   | 6.471      | 4.276      | 1.513      | 9.415      | 3.614     |
| MAPE    | 1.799   | 1.877      | 1.957      | 2.217     | 3.480      | 2.151      | 3.291   | 17.950    | 1.811      | 1.988      | 3.091      | 5.561      | 3.791     |
| b       | 2.149   | 2.323      | 2.927      | 3.561     | 8.411      | 17.103     | 20.436  | 50.270    | 1.964      | 1.058      | -0.363     | 2.878      | 1.055     |

Table A3. Mean absolute percentage error (MAPE) and mean square error (MSE) for oil consumption of BRICS in 1992–2019.

Note: MSE = Mean Standard Error; MAPE = Mean Absolute Percentage Error. The shaded area indicates the best model for a given country.
### Table A4. Mean absolute percentage error (MAPE) and mean square error (MSE) for gas consumption of BRICS in 1992–2019.

| Country | MAPE | MSE | $a$ | $b$ | $r = 0$ | $r = 0.01$ | $r = 0.05$ | $r = 0.1$ | $r = 0.5$ | $r = 0.9$ | $r = 1$ | $r = 1.5$ | $r = -0.01$ | $r = -0.05$ | $r = -0.1$ | $r = -0.5$ | $r = -0.9$ | $r = -1.5$ |
|---------|------|-----|-----|-----|--------|-----------|-----------|-----------|-----------|-----------|--------|--------|------------|------------|------------|------------|------------|------------|------------|
| Brazil  |      |     |     |     |        |           |           |           |           |           |        |        | FGM (1, 1) | ARIMA(1, 1) |            |            |            |            |            |
| MSE     | 13.971 | 13.862 | 13.461 | 13.031 | 11.422 | 15.033 | 17.749 | 60.883 | 14.085 | 14.589 | 15.360 | 42.822 | 58.652 | 2234.459 | 4.822 |
| MAPE    | 22.107 | 22.113 | 22.170 | 22.262 | 24.350 | 29.581 | 31.343 | 43.135 | 24.350 | 22.101 | 22.173 | 22.340 | 31.303 | 66.971 | 278.951 | 9.528 |
| $a$     | 0.008 | 0.007 | 0.004 | -0.001 | -0.035 | -0.062 | -0.068 | -0.092 | 0.009 | 0.012 | 0.016 | 0.007 | 0.006 | 0.108 | —           | —          |
| $b$     | 1.166 | 1.192 | 1.300 | 1.441 | 2.972 | 5.820 | 6.883 | 16.021 | 1.140 | 1.038 | 0.915 | 0.072 | -0.104 | -0.090 | —           | —          |
| China   |      |     |     |     |        |           |           |           |           |           |        |        | FGM (1, 1) | ARIMA(1, 1) |            |            |            |            |            |
| MSE     | 2386.569 | 2286.868 | 1933.065 | 1576.655 | 422.742 | 236.068 | 233.796 | 455.330 | 2491.238 | 2964.885 | 3703.170 | 22144.398 | 49126.530 | 63696.575 | NA         | NA         |
| MAPE    | 60.179 | 58.943 | 54.298 | 49.114 | 26.881 | 19.728 | 18.884 | 19.937 | 61.446 | 66.841 | 74.376 | 175.801 | 310.116 | 473.308 | NA          | NA         |
| $a$     | -0.108 | -0.108 | -0.108 | -0.109 | -0.115 | -0.122 | -0.124 | -0.133 | -0.108 | -0.107 | -0.107 | -0.098 | -0.054 | 0.067 | —           | —          |
| $b$     | 0.756 | 0.787 | 0.920 | 1.101 | 3.377 | 8.018 | 9.794 | 25.724 | 0.725 | 0.608 | 0.477 | -0.092 | -0.046 | -0.445 | —           | —          |
| India   |      |     |     |     |        |           |           |           |           |           |        |        | FGM (1, 1) | ARIMA(1, 1) |            |            |            |            |            |
| MSE     | 18.215 | 18.125 | 17.824 | 17.565 | 18.099 | 22.225 | 24.800 | 82.087 | 18.312 | 18.766 | 19.530 | 158.415 | 176.382 | 2806.706 | 4.925 |
| MAPE    | 8.607 | 8.498 | 8.143 | 7.842 | 8.005 | 10.882 | 12.105 | 22.167 | 8.727 | 9.325 | 10.433 | 45.288 | 49.903 | 178.481 | 4.435 |
| $a$     | -0.002 | -0.002 | -0.001 | -0.001 | -0.018 | -0.040 | -0.046 | -0.070 | -0.003 | -0.003 | -0.008 | 0.028 | 0.262 | 0.551 | —           | —          |
| $b$     | 1.364 | 1.432 | 1.709 | 2.072 | 5.985 | 13.333 | 16.108 | 40.412 | 1.298 | 1.040 | 0.738 | 0.142 | 0.278 | -0.408 | —           | —          |
| Russia  |      |     |     |     |        |           |           |           |           |           |        |        | FGM (1, 1) | ARIMA(1, 1) |            |            |            |            |            |
| MSE     | 1597.445 | 1070.673 | 199.004 | 149.132 | 594.394 | 338.965 | 211.700 | 6941.837 | 1708.874 | 804.480 | 274.693 | 262.158 | 1829.579 | 668.162.502 | 133.125 |
| MAPE    | 13.971 | 13.862 | 13.461 | 13.031 | 11.422 | 15.033 | 17.749 | 60.883 | 14.085 | 14.589 | 15.360 | 42.822 | 58.652 | 2234.459 | 4.822 |
| $a$     | 0.008 | 0.007 | 0.004 | -0.001 | -0.035 | -0.062 | -0.068 | -0.092 | 0.009 | 0.012 | 0.016 | 0.007 | 0.006 | 0.108 | —           | —          |
| $b$     | 1.166 | 1.192 | 1.300 | 1.441 | 2.972 | 5.820 | 6.883 | 16.021 | 1.140 | 1.038 | 0.915 | 0.072 | -0.104 | -0.090 | —           | —          |
| South Africa | | | | | | | | | | | | | | | |
| MSE     | 48.536 | 47.852 | 45.358 | 42.625 | 31.557 | 30.042 | 30.360 | 34.505 | 49.252 | 52.327 | 56.664 | 93.233 | 100.429 | 353.199 | 13.235 |
| MAPE    | 8.607 | 8.498 | 8.143 | 7.842 | 8.005 | 10.882 | 12.105 | 22.167 | 8.727 | 9.325 | 10.433 | 45.288 | 49.903 | 178.481 | 4.435 |
| $a$     | -0.002 | -0.002 | -0.001 | -0.001 | -0.018 | -0.040 | -0.046 | -0.070 | -0.003 | -0.003 | -0.008 | 0.028 | 0.262 | 0.551 | —           | —          |
| $b$     | 1.364 | 1.432 | 1.709 | 2.072 | 5.985 | 13.333 | 16.108 | 40.412 | 1.298 | 1.040 | 0.738 | 0.142 | 0.278 | -0.408 | —           | —          |

**Note:** MSE = Mean Standard Error; MAPE = Mean Absolute Percentage Error. The shaded area indicates the best model for a given country.
### Table A5. Mean absolute percentage error (MAPE) and mean square error (MSE) for coal consumption of BRICS in 1992-2019.

|                  | FGM (1, 1) for Brazil | ARIMA(1, 1)  |
|------------------|-----------------------|--------------|
| \( r = 0 \)      | 3.022                 | 0.05         |
| MSE              | 3.040                 | 0.01         |
| MAPE             | 3.128                 | 0.05         |
| \( r = 0.05 \)   | 3.245                 | 0.10         |
| MSE              | 3.364                 | 0.50         |
| MAPE             | 3.726                 | 0.90         |
| \( r = 0.1 \)    | 3.068                 | 0.90         |
| MSE              | 2.980                 | 0.90         |
| MAPE             | 11.746                | 0.90         |
| \( r = 0.5 \)    | 3.007                 | 0.90         |
| MSE              | 3.095                 | 0.90         |
| MAPE             | 4.226                 | 0.90         |
| \( r = 0.9 \)    | 8.160                 | 0.90         |
| MSE              | 8.410                 | 0.90         |
| MAPE             | 8.704                 | 0.90         |
| \( r = 1 \)      | 8.823                 | 0.90         |
| MSE              | 14.57                 | 0.90         |
| MAPE             | 8.404                 | 0.90         |
| \( r = 0.01 \)   | 14.936                | 0.90         |
| MSE              | 19.536                | 0.90         |
| MAPE             | 8.106                 | 0.90         |
| \( r = 0.05 \)   | 15.866                | 0.90         |
| MSE              | 12.508                | 0.90         |
| MAPE             | 8.484                 | 0.90         |
| \( r = 0.1 \)    | 22.304                | 0.90         |
| MSE              | 15.261                | 0.90         |
| MAPE             | 12.653                | 0.90         |
| \( r = 0.5 \)    | 11.424                | 0.90         |
| MSE              | 13.056                | 0.90         |
| MAPE             | 28.945                | 0.90         |
| \( r = 0.9 \)    | 27.770                | 0.90         |
| MSE              | 28.406                | 0.90         |
| MAPE             | 13.056                | 0.90         |
| \( r = 1 \)      | 37.475                | 0.90         |
| MSE              | 37.702                | 0.90         |
| MAPE             | 28.406                | 0.90         |
| \( r = 0.01 \)   | 37.702                | 0.90         |
| MSE              | 41.620                | 0.90         |
| MAPE             | 43.382                | 0.90         |
| \( r = 0.05 \)   | 31.570                | 0.90         |
| MSE              | 40.767                | 0.90         |
| MAPE             | 43.544                | 0.90         |
| \( r = 0.1 \)    | 31.570                | 0.90         |
| MSE              | 17.531                | 0.90         |
| MAPE             | 31.570                | 0.90         |
| \( r = 0.5 \)    | 23.058                | 0.90         |
| MSE              | 28.406                | 0.90         |
| MAPE             | 28.406                | 0.90         |
| \( r = 0.9 \)    | 14.400                | 0.90         |
| MSE              | 17.494                | 0.90         |
| MAPE             | 17.494                | 0.90         |
| \( r = 1 \)      | 17.494                | 0.90         |
| MSE              | 392.652               | 0.90         |
| MAPE             | 392.652               | 0.90         |
| \( r = 0.01 \)   | 17.494                | 0.90         |
| MSE              | 18.127                | 0.90         |
| MAPE             | 18.127                | 0.90         |
| \( r = 0.05 \)   | 39.026                | 0.90         |
| MSE              | 28.406                | 0.90         |
| MAPE             | 28.406                | 0.90         |
| \( r = 0.1 \)    | 28.406                | 0.90         |
| MSE              | 13.971                | 0.90         |
| MAPE             | 13.971                | 0.90         |
| \( r = 0.5 \)    | 14.936                | 0.90         |
| MSE              | 14.936                | 0.90         |
| MAPE             | 14.936                | 0.90         |
| \( r = 0.9 \)    | 15.866                | 0.90         |
| MSE              | 15.866                | 0.90         |
| MAPE             | 15.866                | 0.90         |
| \( r = 1 \)      | 22.104                | 0.90         |
| MSE              | 22.104                | 0.90         |
| MAPE             | 22.104                | 0.90         |
| \( r = 0.01 \)   | 8.106                 | 0.90         |
| MSE              | 8.106                 | 0.90         |
| MAPE             | 8.106                 | 0.90         |
| \( r = 0.05 \)   | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.1 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.5 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.9 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 1 \)      | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.01 \)   | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.05 \)   | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.1 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.5 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 0.9 \)    | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |
| \( r = 1 \)      | 7.322                 | 0.90         |
| MSE              | 7.322                 | 0.90         |
| MAPE             | 7.322                 | 0.90         |

**Note:** MSE = Mean Standard Error; MAPE = Mean Absolute Percentage Error. The shaded area indicates the best model for a given country.
### Table A6. Mean absolute percentage error (MAPE) and mean square error (MSE) for hydropower consumption of BRICS in 1992–2019.

|                      | FGM (1, 1) for Brazil | ARIMA(1, 1, 1) |
|----------------------|-----------------------|----------------|
| **MSE**              | 26.193                | 12.919         |
| **MAPE**             | 4.903                 | 3.7851         |
| a                    | 0.067                 | 0.005          |
| b                    | 6.286                 | 14.13         |
| r = 0                | 5.671                 | 5.531          |
| r = 0.01             | 8.768                 | 5.311          |
| r = 0.05             | 8.602                 | 5.410          |
| r = 0.1              | 8.617                 | 5.421          |
| r = 0.5              | 8.782                 | 5.410          |
| r = 0.9              | 8.617                 | 5.421          |
| r = 1                | 8.782                 | 5.410          |
| r = 1.5              | 8.782                 | 5.410          |
| r = −0.01            | 8.782                 | 5.410          |
| r = −0.05            | 8.782                 | 5.410          |
| r = −0.1             | 8.782                 | 5.410          |
| r = −0.5             | 8.782                 | 5.410          |
| r = −0.9             | 8.782                 | 5.410          |
| r = −1.5             | 8.782                 | 5.410          |

**Note:** MSE = Mean Standard Error; MAPE = Mean Absolute Percentage Error. The shaded area indicates the best model for a given country.
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