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Forecast Models Derived by Trend Analysis for the BRICS Economies' Primary Energy Consumption

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ABSTRACT

In this study, trend analysis-based forecast models were derived for the primary energy consumptions (PECs) of Brazil, the Russian Federation, India, China and South Africa economies, known as the BRICS worldwide using total population (TP) and PECs as independent and dependent variables from 1985 to 2023. The established models were then statistically verified by several indices. A variety of error indicators were also employed to assess the forecasting accuracies of the established models. Additionally, the PECs of the BRICS economies were projected from 2025 to 2035 using the proposed models. The results reveal that the future PECs of the related economies can be successfully projected with the proposed models. Moreover, the forecasting results make it abundantly evident that substantial rises are anticipated for the related economies' future PECs. It is thought that the study's results will allow the way for the proposal and establishment of sustainable strategies for controlling the PECs of the BRICS economies using the proposed methodology.

BRICS Ekonomilerinin Birincil Enerji Tüketimi için Trend Analiziyle Türetilen Tahmin Modelleri

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ÖZ

Bu çalışmada, dünya çapında BRICS olarak bilinen Brezilya, Rusya Federasyonu, Hindistan, Çin ve Güney Afrika ekonomilerinin birincil enerji tüketimleri (PEC) için 1985'ten 2023'e kadarki toplam nüfus (TP) ve birincil enerji tüketimleri (PEC) bağımsız ve bağımlı değişkenler olarak kullanılarak trend analizi tabanlı tahmin modelleri türetilmiştir. Türetilen modeller daha sonra çeşitli indisler ile istatistiksel olarak doğrulanmıştır. Aynı zamanda, oluşturulan modellerin tahmin doğruluklarının değerlendirilmesi için çeşitli hata göstergeleri de kullanılmıştır. Ek olarak, BRICS ekonomilerinin PEC'leri önerilen modeller kullanılarak 2025'ten 2035'e kadar tahmin edilmiştir. Sonuçlar, ilgili ekonomilerin gelecekteki PEC'lerinin önerilen modellerle başarılı bir şekilde tahmin edilebileceğini ortaya koymuştur. Ayrıca, tahmin sonuçları ilgili ekonomilerin gelecekteki PEC'lerinde önemli artışların beklendiğini açıkça göstermiştir.

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1. Introduction

Energy is one of the most important factor in developing and achieving the sustainable economic growth of any country. It can be assessed in many forms and its sources can be classified into three main categories as fossil, renewable and fissile (Gazder, 2016; Wang et al., 2022a). Among these energy sources, the fossil fuels (FFs) account for a sizable portion in the world's overall energy supply. They accounted for more than 80% of the world's primary energy consumption (PEC). In other words; oil, natural gas and coal were responsible for 32%, 24% and 27% of the world's total PECs, while those were 6%, 8% and 4% for the hydroelectric, renewables and nuclear respectively in 2023. China, whose PEC reached to 171 exajoule was the global leader in PEC in 2023. This was almost equal to total PECs of the United States (US), India and the Russian Federation which were ranked as second, third, and fourth in PECs respectively in 2023 worldwide (EI, 2024). Even though the FFs still account for the majority of the world's energy requirements, the renewable energy (RE) has recently gained popularity as a global clean energy investment as well.

Apart from 2009 and 2020, the global PEC increased annually throughout the previous 20 years. It experienced a downward trend in 2009 and 2020 due to the impact of the worldwide economic downturn and the Covid-19 respectively. During the Covid-19 especially, lockdown procedures and a decrease in business activity negatively affected the PEC. As a result, global PEC growth declined by 4.5% in 2020, except in China that recovered quickly from the defined catastrophe. 2.2% was the increase in China's PEC, a substantially slower rate than in prior years (+4% annually from 2008 to 2018 and +3.8% in 2019). Significant declines were seen in the US (-7.7%), the European Union (EU) (nearly 8%, with notable declines in the major markets of Germany, France, Italy, and Spain), Japan (7.5%), roughly Canada (6%), and the Russian Federation (5.5%). There was less of a decline in South Korea by 4%, and even lower (around -1.4%) in Saudi Arabia and 3.6% Brazil. Africa and the Middle East saw contractions for the PEC as well (EI, 2024). Following declining trend in 2020, the world PEC has begun to increase again in 2023 worldwide and it is expected to grow dramatically in the future years (almost 50% towards 2050). Growing economies including Brazil, India, China, Türkiye, Indonesia, Bangladesh and more are expected to experience the biggest growth (IPCC, 2013; BP, 2020; Chiu and Lee, 2020; IEA, 2021; BP, 2023).

Given that the importance of energy for both global and domestic economic growths (especially the FFs), it is possible to say that many scholars and a wide range of organizations have extensively looked into a variety of strategies to improve and correct the PEC models by switching to alternative fuels. Additionally; there is a need to provide reliable forecasting about PEC across its different sources either regionally or nationally. Similarly, given that a precise estimate of total PEC indicates a favorable influence on assessing the future trend, countries can identify environmentally friendly approaches that comprise reducing energy waste as well as boosting energy conservation to promote long-term economic growth (Pao and Tsai, 2021; Wang et al., 2022a). Consequently, as there is broad agreement among academics, researches into creating and enhancing forecasting models' efficacy have never ceased because the risk of uncertainties in making decisions may be decreased by more forecasting models. This is why; based on total population, this study focuses on the trend analysis (TA)-based forecast models for the PECs of the BRICS economies.

2. Evaluation of the Relevant Literature

Enormous researches can be found in the existing literature, studying and utilizing different modeling and forecasting techniques. Various studies have also tested these techniques for energy production/consumption using a variety of data sets from various countries or regions over various time periods. Some recent examples of these studies concentrating on the PEC are as follows. Gazder (2016) presented comparison on Saudi Arabia and Pakistan regarding their PECs and the variables influencing them and proposed predictive models to forecast their PECs till 2040 using regression analysis. The link between economic growth and the PEC was explored by Pedroni cointegration test, the second-generation panel cointegration test, Westerlund and Edgerton test and FMOLS test for BRICS-T countries (Yildirim and Yildirim, 2019). On the basis of data from the G-7 and the N-11 countries for the period from 1990 to 2016, Zafar et al. (2019) probed the relationship between carbon emissions and disaggregated financial development and REC using second generation unit roots testing. Analyzing the links between economic growth, fossil fuel use, CO_2 emissions and oil prices in 54 African countries according to a PMG panel ARDL methodology was carried out by Mensah et al. (2019). The nexus between PEC and economic growth in Tanzania was empirically analyzed on the basis of Engel and Granger tests (Simba and Oztek, 2020). Karakurt (2020) proposed regression models, derived from the social and economic variables of BRICS-T countries to forecast the PECs in the related countries. In another study, BRICS-T countries' oil consumption was modelled and forecasted through proposed predictive models (Karakurt, 2021). Khan and Osinska (2021) proposed predictive models for forecasting the PECs in BRICS utilizing the annual time series data set from 1992 to 2019 as the foundation for a novel FGM with various order parameters, both at the aggregate and disaggregate levels. Konuk et al. (2021) investigated how the next eleven countries' economies (except for Vietnam) and BEC correlated employing the annual data covering the years 1970–2017 were used to perform panel data analysis. Ehigiamusoe and Dogan (2022) used empirical estimations to examine the effects of real income, renewable energy, and their interaction effect on carbon emissions in low-income countries. Zeeshan et al. (2022) compared the nexus among CO_2 emissions, PEC, trade liberalization and economic growth in Latin American and Southeast Asian nations using structural equation modeling technique. Chang and Fang (2022) investigated empirically the effect of REC on the growth of the economies of the N-11 and BRICS using MMQR and AMG methods. The role of PEC, environmental deterioration in the top five carbon emitting countries from fossil, nuclear and renewable energy sources was empirically investigated through multivariate adaptive regression splines (Kartal, 2022). Evidence from Autoregressive distributed lagged in error correction approach was presented for the determinants of REC in Nigeria (Somoye et al., 2022). An innovative time-delay grey model employing mixedfrequency data to predict China's PEC was applied by Wang et al. (2022a). Fareed and Pata (2022) employed recently developed Fourier panel cointegration and causality tests to examine the effects of renewable and non-REC on economic growth in the top ten countries that consume renewable energy between 1970 and 2019. Lorente et al. (2022) verified the EKC and PH hypotheses in order to examine the relationship between BRICS countries' economic growth, urbanization, PEC, and carbon emissions between 1990 and 2014. Wang et al. (2022b) developed a conceptual framework using the Dumitrescue-Hurlin test to look at the causal relationship between variables and the Driscolle-Kraay test to estimate the long-term coefficient in order to investigate the moderating role of financial development in the REC-CO_2 emissions linkage for the Next 11 countries from 1990 to 2015. The relationship between foreign direct investment, BEC and air pollution was analyzed by means of a panel data analysis for the BRICS countries from 1992 to 2017 (Tuzemen and Tuzemen, 2022). PEC in Turkiye was analyzed using ANN method and PEC forecast for 2021–2025 was made (Demircioglu and Esiyok, 2022).

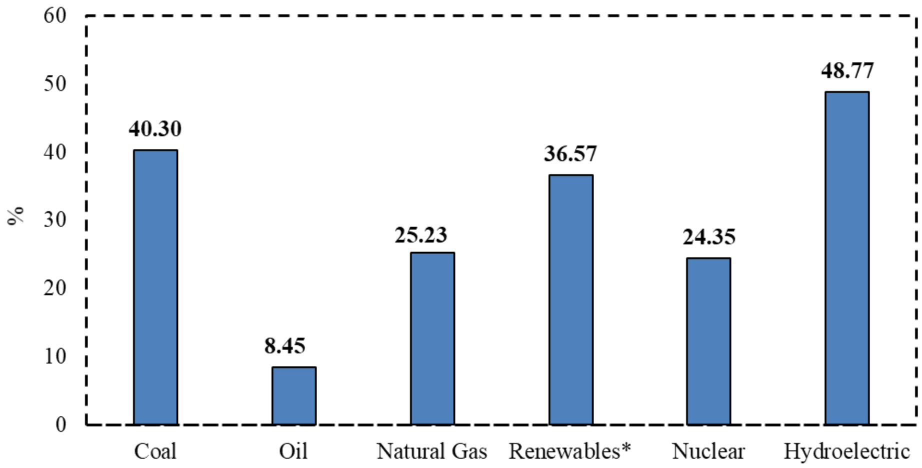
2.1. Novelty of the study

There are, of course, many modeling and estimating techniques for developing and/or proposing predictive models in the literature. Several factors, including the number of variables, practicality, and usage purposes, can determine which of these is preferred. While these modeling techniques are advantageous in that they can precisely describe the phenomenon of long-term trends, upon construction and applying the models to actual situations, they can exhibit certain limitations. In this instance, less precise and more straightforward modeling approaches might be valued, particularly if it just serves as a part of a more complex tool for planning (Bianco et al., 2009). In contrast to other methods those require numerous parameters and are far more complex, linear and nonlinear modelling technique, also called as TA technique, presents a notion that readers can infer future events from what has happened in the past. In other words; the TA presents the data's evolution from the past to the present and makes some forecasts for upcoming planning easier (Celiker et al., 2021). In addition, this approach's primary benefit is its simplicity, and projections are made using whatever data is available (Kone and Buke, 2010). Moreover, the followings enumerate the advantages of the TA over alternative forecasting modelling techniques. First, a regression toolbox is available in practically all statistical software, creating models is simple using TA which is inside the regression toolbox. Second, given that the expression of the dependent variable is a function of the independent variables, simpler and more understandable model could be derived. Third, unlike artificial intelligence applications, it doesn't have any black box features that would obscure the structure of the function being approximated when creating a model. Fourth, once the final formula has been established, it can be used for any projection or scenario. Moreover, and the most importantly, no studies to date focused on the relationship between the PECs and total population in the BRICS countries in the relevant literature. Thus, this study aims at filling the aforementioned gap and presents more practical predictive models.

3. BRICS (Brazil, the Russian Federation, India, China and South Africa) economies

Goldman Sachs chief economist Jim O'Neill propounded an acronym as BRIC for the developing nations of Brazil, Russia, India, and China on the basis of their common progress of macroeconomic and demographic indicators in 2001. In 2010, then South Africa joined officially to the group and the acronym became as BRICS. As of January 2024, five additional nations including Egypt, Ethiopia, Iran, the United Arab Emirates, and Saudi Arabia, have formally joined the group known as BRICS since 2010. It is expected that the group will be renamed "BRICS+" with the additional members, though this is not yet known (Ergezer, 2025). On one hand; since Jim O'Neill coined the BRIC acronym in the early 2000s, the number of appealing categories for developing/emerging market nations has skyrocketed. MINT, EAGLE, CIVETS and N–11 or Next – eleven are some of the widely used abbreviations for economies in developing/emerging markets (Cambazoglu, 2021; PwC, 2024). Although they are the world's fastest growing economies, the BRICS countries vary greatly in terms of geographical location and availability of natural resources, rate of development and economic growth as well. Because of these outstanding features, studying on the BRICS countries is crucial to propose policies for achieving sustainable development as the international organizations. Demographically, the BRICS nations have currently over a total population of 3 billion people, representing around 40 percent of global population, 39% of world urbanization rate, representing roughly 26 trillion US dollars GDP, or 26% of the global economy. These nations also occupy a 30% of total surface of Earth. Additionally, the BRICS economies had higher annual growth rate than the world's average, which was 2.72%. India recorded the highest growth at an annual rate of 7.58%, while South Africa was the lowest performing BRICS economies. There was just one country, the Russian Federation that was witnessing economic decline. When it comes to human development, it can be noted that the Russian Federation is ranked fairly high among the group, while India and others are respectively in the medium and the high human development categories. Furthermore, by 2050, it is projected that the GDPs of nearly all BRICS nations will have advanced to a high position, except the Russian Federation. For example, in terms of nominal GDP expressed in US dollars, China is predicted to surpass the US in 2030 and continue to lead the world economy through 2050 (Zakarya et al., 2015; WBI, 2025). Conclusively, recent projections suggest that the BRICS countries will be the world's most powerful economies by 2030 (Azevedo et al., 2018; Gusarove, 2019; Chang and Fang, 2022). Thus, the BRICS countries have recently attracted a lot of attention from researchers due to their socio-economic characteristics and influential in global markets. As the developing economies, the BRICS nations also hold important positions in the global energy balance in terms of their energy resources and consumptions. As seen in Figure 1, this group has significant energy resources. In other words; around 8.5 percent, 25 percent, and 40 percent of the known reserves of oil, natural gas and coal respectively in the world are located in the BRICS countries. In terms of the FF resources, the leader countries among the BRICS countries are China, India and the Russian Federation. Apart from FFs, it is evident from Figure 1 that the BRICS countries possess also substantial nuclear, hydroelectric, and renewable energy resources as well. As it can be followed, these countries account for over 45% and 35% of the global hydropower, and renewables respectively, and around 25% nuclear resources. Concerning nuclear, hydropower, and renewable energy sources, China holds a substantial share among the BRICS countries. China is accompanied by Brazil in hydropower, India in renewable energy sources, and the Russian Federation in nuclear power.

Besides significant energy resources, growing PECs are another distinguishing feature of the BRICS countries. A sizeable portion of the worldwide PEC results from of these countries. In 2023, the total PECs of the BRICS countries was 260 exajoules, while the world's PEC was 620 exajoule. Put differently, the BRICS countries accounted for almost 42% of the world's total PEC (Figure 2). China, India and the Russian Federation were the top three BRICS countries that contributed most to these rates, placing them at the forefront.



* Includes geothermal, biomass and other sources of renewable energy (not already itemized)

Figure 1. Current status of the energy resources of the BRICS economies (EI, 2024)

4. Modelling approach

4.1. Data

The PEC and total population (TP) data for the years 1985–2023 are used in this study, with the exception of the Russian Federation. Founded after the collapse of the Soviet Union in the 1990s, data for the Russian Federation are available as of 1990. Therefore, the Russian Federation has been excluded from the study. Additionally, the new members of the BRICS have also been not included in the study. The data were collected from the officially and freely available on line sources (EI, 2024; WBI, 2025). Since the TP and energy requirements have a strong correlation, and their time series are readily accessible in a variety of statistical databases, the TP was utilized as the independent variable. Additionally; for variable selection, this research followed the previous research studies of Kavaklıoğlu et al. (2009) and Kankal et al. (2011) since they state that population growth raises the demand for energy resources due to a variety of human activities. Descriptive statistics, performed on raw data which are PEC and TP, are recorded in Table 1. It descriptively reveals that the PEC (exajoule) and TP (million) on average are 60.99 and 1242.913 that are really substantial respectively for China. Although the largest average value of the TP belongs to China, the SD of the TP for India shows the largest deviation among BRICS nations. It reflects as 162.42 exhibiting variance as determined by the CV, which is obtained by dividing SD by the mean of 15.41. On the other hand; for an observed series to be considered symmetric or normally distributed, the normal values for kurtosis and skewness must be zero (the ideal one).

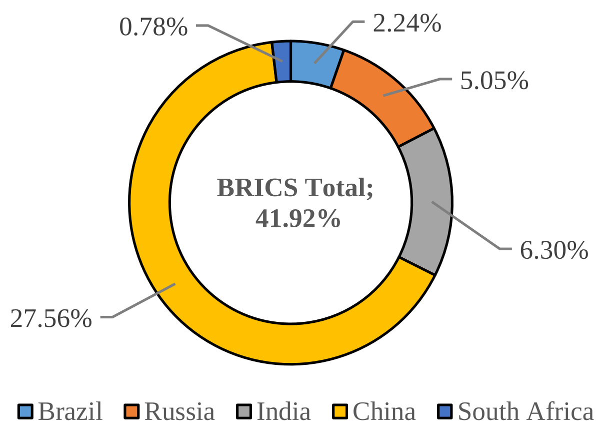


Figure 2. Share of the BRICS economies' PECs in the world (EI, 2024)

Nonetheless, some academics contend that the observed series is also comparable to a normal distribution if both values fall within ±1.5 (Tabachnick and Fidell, 2013; Erba and Beydogan, 2017). Based on the skewness and kurtosis in Table 1, the results suggest that every observed series has a normal distribution. In particular, values based on skewness indicate that the PEC variable is positively skewed, which means that all of the countries' variables are biased to the right. In contrast, the variable TP is skewed negatively.

Table 1. Results for the descriptive statistics

Nations	Series	Min	Max	Mean	SD	CV (%)	Skewness	Kurtosis	JB test
Brazil	**PEC**	4.94	12.83	8.43	2.49	29.54	0.35	-1.07	0.348
	TP	135.274	204.471	172.897	21.24	12.29	-0.21	-1.21	0.347
India	**PEC**	5.70	28.55	14.71	6.77	46.02	0.60	-0.75	0.274
	TP	784.360	1310.152	1053.809	162.42	15.41	-0.05	-1.25	0.362
China	**PEC**	22.14	126.49	60.99	35.44	58.11	0.69	-1.07	0.140
	TP	1051.040	1379.860	1242.913	96.85	7.79	-0.47	-0.90	0.335
South Africa	**PEC**	3.29	5.27	4.35	0.66	15.08	0.05	-1.39	0.285
	TP	32.679	55.386	44.377	6.65	14.98	-0.15	-1.04	0.469

CV: the coefficient of variation (%), SD: the standard deviation; JB: the statistic of the Jarque-Bera (JB) test normality ($p >$ 0.05 presents the normality of series).

Additionally, based on the kurtosis results, every variable has a kurtosis value that is lower than the normal value (≤±3) giving evidence that this distribution's kurtosis curve is platykurtic. That is, data are dispersed over a larger area and have a slightly flatter distribution than normal. Conclusively, the results of skewness and kurtosis affirm that every variable follows a normal distribution. This is consistent with the normalcy test conducted by Jarque-Bera (JB) offering compelling proof that every observed series has a normal distribution because of the JB test's highest p-values ($p>0.05$). Therefore, it may be concluded that the data generally supports linearity, one of the core tenets of the regression model put out by Ostrom (1978).

4.2. Methodology

We utilized the TA to establish and propose the forecasting models for the PECs in the BRICS countries. This technique makes use of the past correlation between a dependent and independent variable to propose predictive models for forecasting the dependent variable's future values. In the analysis, the assumption is that future PEC and TP will be in line with historical trends. The main advantage of this method is that it is straightforward and uses whatever data is available to make projections (Aydin, 2015; Aydin et al., 2015; Kok and Benli, 2017). The equation forms for the TA that were used in the study, are explained as linear, logarithmic, power, exponential, inverse, growth and S functions. The data were split into two sets: one set was used to train the model between 1985 and 2015 (74.2%), and the other set was used to test it between 2016 and 2023 (24.8%). The SPSS software, providing an option for regression, was applied for establishing the forecasting models. Following model development, a variety of statistical tests were used to confirm the generality, plausibility and statistical significance of the estimated variables such as R^2, assessing how well a model fits actual data points, or a metric that indicates the model's degree of prediction, F – and t tests to confirm that the independent and dependent variables having meaningful relationships and to evaluate the strength of each model coefficient individually, and examining the predicted versus actual trends respectively. The R^2 is used as a standard to evaluate the correctness of the model, in addition to providing how much of the variance of one variable may be anticipated from another. Higher R^2 values suggest a more trustworthy model. In other words; since it fluctuates between 0 and 1, the latter of which indicates that the data and the fitted curve points have a perfect linear functional connection, but, the first indicates the opposite as noted by Aydin (2014) and Despotovic et al. (2015). Two important tests that have a direct impact on the models' significance and confidence intervals of the models are the F and t tests respectively in statistical inference and coefficients and finally, the conclusions drawn from testing the hypotheses. When the computed F- and t-values surpass the tabulated F- and t-values, the model's validation is verified Aydin (2014). It implies, in other words, that every independent variable in the model is significant and that there is a substantial link between the dependent and independent variables. Moreover; robustness and/or accuracies of the derived models was measured in order to choose the most effective forecasting model, following the verification of the derived models. The statistical indices that were used to assess the robustness of the established models are displayed in Table 2 with their mathematical illustrations. Whatever the performance criterion, the fitted curve often more closely matches the real data the lower the criterion's value (Uma et al., 2011). Stated differently, the forecasting model's accuracy increases with decreasing values of the statistical indices. On the other hands; a pair of measures of the average magnitude of absolute projected errors are the MAD and MSE (Paiva et al., 2021), while the RMSE measures the change in the estimated values around the measured data and provides information on the performance over the short period of time. As an another error indicator, The RRMSE serves to measure the overall relative accuracy of a model. Additionally, the U_{95} shows more information about the model deviation as well (Azadeh et al., 2011; Bianco et al., 2014). Furthermore, the research flowchart can be seen in Figure 3.

Table 2. Criteria for evaluating the correctness of the models

Mean absolute deviation	$MAD = \left(\frac{1}{n}\sum_{i=}^{n}\lvert X_i - Y_i\rvert\right)$
Root mean square error	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2}$
Relative root mean square error	$RRMSE = \frac{RMSE}{\bar{O}}.100$
Uncertainty at 95%	$U_{95} = (1.96).[(SD^2 + RMSE^2)]^{1/2}$
Maximum absolute relative error	$erMAX = max\left(\left\lvert\frac{X_i - Y_i}{Y_i}\right\rvert\right)$
Mean absolute percentage error	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\lvert X_i - Y_{i)}\rvert}{Y_i}\right).100$
where; n is the total number of data, X_i is the predicted PEC, Y_i is the actual PEC, $\bar{O}$ is the mean value of observed data	

5. Results and Discussion

5.1. Derived models and validation

Forecasting models based on the TP are provided in Table 3. Models in all equation forms were firstly derived for all nations and then, the models in Table 3 were selected, based on their mainly lowest MAPE and RRMSE values. As it can be followed from Table 3, the derived models for China and India are explained as the power functions, while those are linear function for Brazil and inverse function for South Africa. Based on the verification results in Table 4, it is evident that a strong degree of association between the TP and PEC is indicated by the proposed models' R^2 values, which are greater than 0.90, apart from the R^2 values of China whose R^2 is 0.89. Additionally, the calculated F and t values for each model are significantly greater than the tabular ones as seen in Table 4. These results confirm that, at a 95% confidence level, all of the equations and individual variables involved in the derived models are statistically significant. Furthermore, looking at predicted versus actual trends as indicated in Figure 4, overall, it may be concluded that at the predicted and actual PECs have a strong correlation, demonstrating the ability of the derived models to provide accurate PEC forecasts for the study's conditions. In summary, these findings demonstrate the statistical significance of the associated models.

Table 3. The best forecast models among those derived

Countries	Functions	Equations
Brazil	Linear	$PEC = (-11.340) + (0.114).TP$
India	Power	$PEC = (1.4x10^{-8}).(TP)^{(2.976)}$
China	Power	$PEC = (4.40x10^{-20}).(TP)^{(6.812)}$
South Africa	Inverse	$PEC = (8.288) - (170.861)/(TP)$

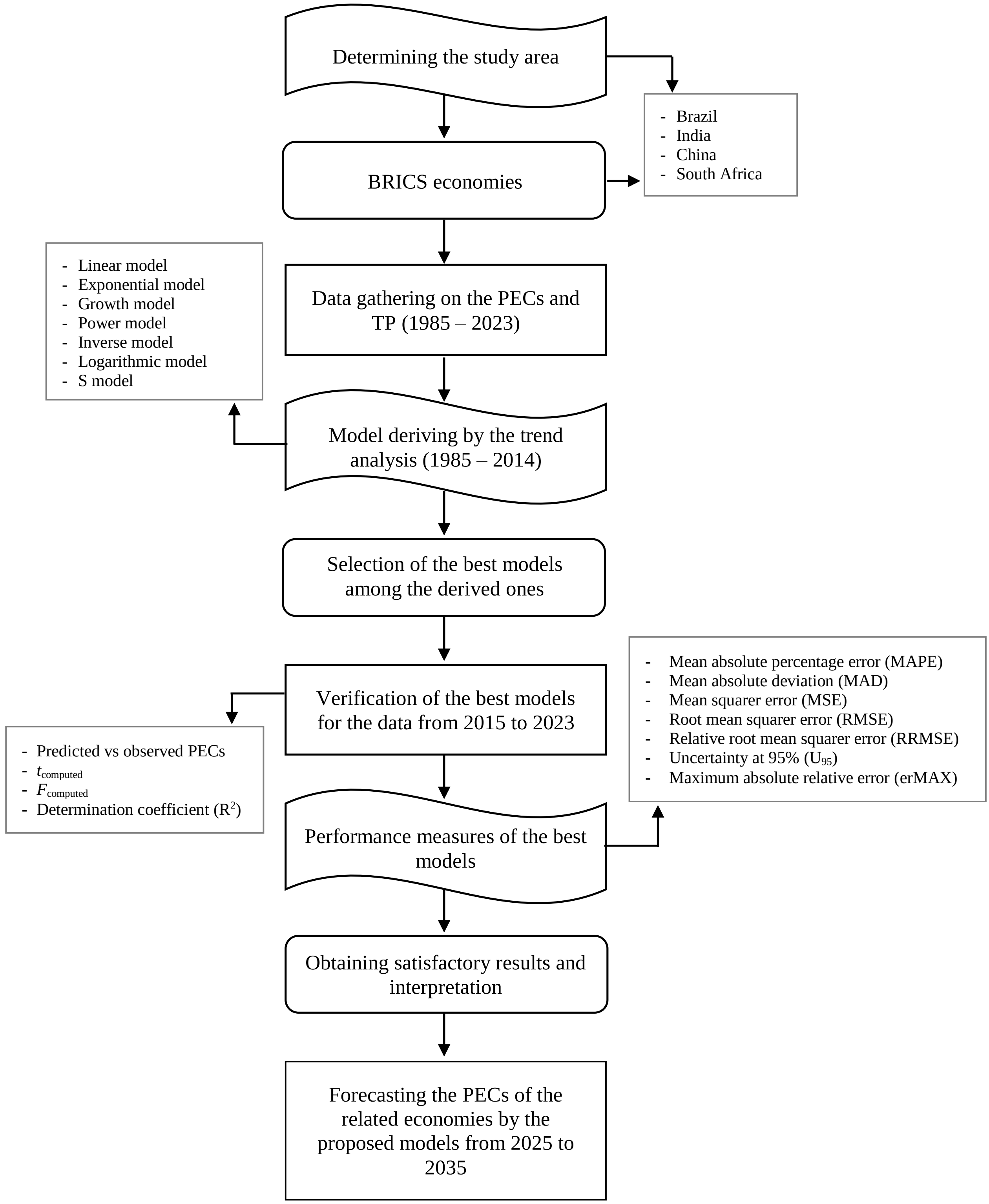


Figure 3. Methodological schema

5.2. Robustness test

In this part, the robustness of the derived models has been highlighted. Among the several performance criteria which were tested in the current study, the MAPE is the most useful tool when estimating relative error since raw data, preprocessed data, and input data used to estimate the model have distinct scales (Azadeh et al., 2011). Kim and Kim (2016) identify the MAPE as one of the most popular statistical metrics for assessing forecast accuracy owing to its benefits of interpretability and scale independence. The MAPE is well-liked by industry practitioners due to its scale independence and ease of interpretation (Byrne, 2012). Because it presents the error as a percentage, this measure is simple to interpret. The usage of absolute percentage errors also solves the issue of positive and negative errors canceling each other out (Bianco et al., 2010; Li et al., 2013). The classifications for the MAPE and RRMSE and the outcomes of the models' performance metrics are provided in Table 5 and Table 6 respectively. Based on the MAPE values, it is obviously noticed that the proposed model for China shows a good forecasting ability, while others have excellent forecasting abilities. Contrary to the MAPE values, it can be clearly seen that the all proposed models indicate the excellent forecasting abilities in terms of the RRMSE values. Additionally, the proposed models indicate high robustness according to other statistical indices as well since their values are close to zero confirming the high predictive capabilities of the proposed models. On the other hand; the current study's robustness results were contrasted with those of a few other studies in the existing literature (Table 7).

Table 4. Statistical results of the proposed models indicating the validation

Countries	Variables	Standard error of estimation	$t_{\text{calculated}}$	t_{table}	$F_{\text{calculated}}$	F_{table}	R^2
Brazil	Constant TP	0.555	-13.637 23.943	1.690	573.291	4.125	0.95
India	Constant TP	0.050	- 50.834	1.690	2584.129	4.125	0.99
China	Constant TP	0.193	- 15.320	1.690	234.703	4.125	0.89
South Africa	Constant TP	0.213	33.222 -15.979	1.690	255.341	4.125	0.90

Table 5. Reference table for the MAPE and RRMSE (Li et al., 2013)

(%)	(%)	Forecasting capability
MAPE ≤ 10	RRMSE < 10	Excellent
11 ≤ MAPE ≤ 20	10 < RRMSE < 20	Good
21 ≤ MAPE ≤ 51	20 < RRMSE < 30	Reasonable
MAPE > 51	RRMSE ≥ 30	Poor

As can be followed, the relative errors were lower for the proposed models. In other words, the proposed models have lower MAPE values, which is an indication that they have high accuracy in comparison to other models developed in the literature.

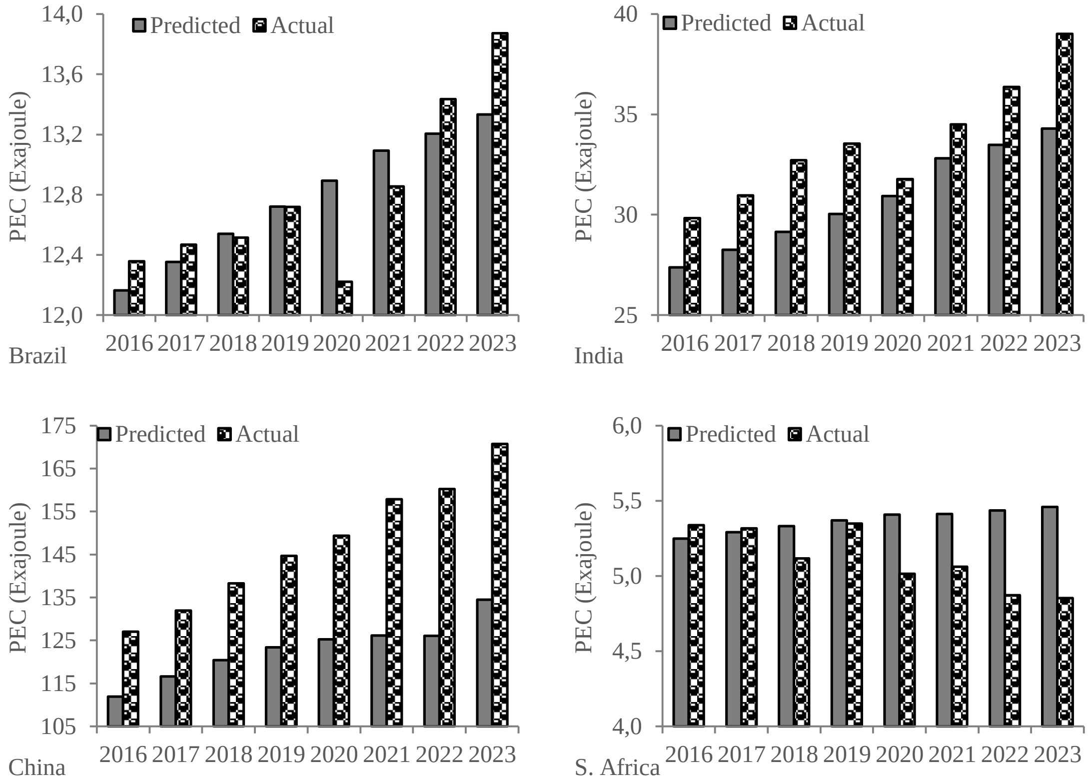


Figure 4. Predicted PECs versus actual PECs for the BRICS economies

Table 6. Error indicators of the proposed models

Countries	Error indicators					
	MAD	RMSE	RRMSE	U_{95}	erMAX	MAPE
Brazil	0.25	0.09	0.73	0.50	0.05	1.96
India	2.80	0.51	1.53	2.55	0.12	8.25
China	22.79	1.95	1.32	15.54	0.21	15.52
South Africa	0.28	0.16	3.14	0.55	0.13	5.70

Table 7. A comparison of the current results with the relevant studies in the literature

Existing literature			This study	
Scholar(s)	Country	MAPE (%)	Country	MAPE (%)
Khan and Osinska (2021)	Brazil	3.43	Brazil	1.96
	South Africa	21.56	South Africa	5.70
Wang et al. (2022b)	China	31.71	China	15.52

5.3. Forecasting results

The future PECs for the BRICS and N-11 nations from 2025 to 2035 are projected by the proposed models. For this purpose, the data of UN (2018) on the TP were utilized. The forecasting results are depicted in Figure 5 together with the historical trend from 1985. Additionally, Figure 6 illustrates that the total PECs of the BRICS countries will amount to 205.05 exajoule in 2035 with a total decrease rate of 10.25% and 0.29% annually, as compared to 2023. Apart from China, the PECs of all the nations are substantially expected to increase towards the year of 2035. As can be followed from Figure 6, a declining trend in the PECs of China is expected for the coming years due to the probably decreasing the TPs of the related nations. Among the BRICS nations, Brazil is projected to see the minimal growth (6.60%). It is noteworthy that a very high increase is expected in the PECs of South Africa.

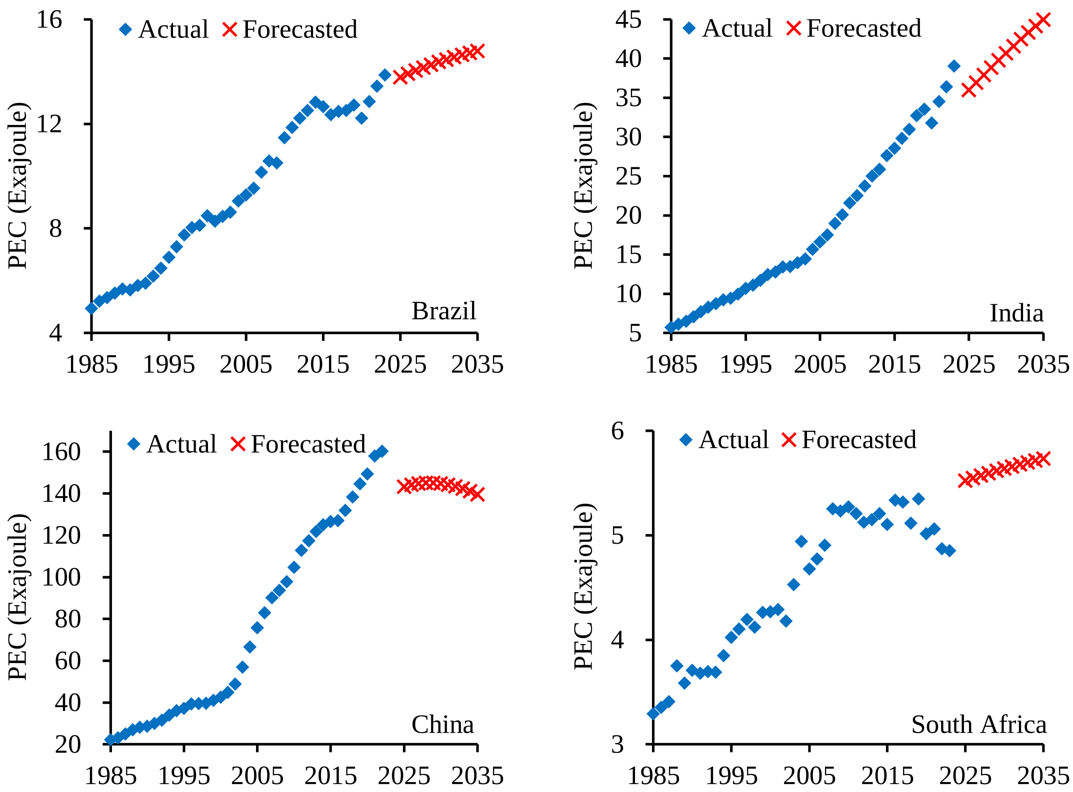


Figure 5. Forecasted PECs for the BRICS economies

That means, South Africa's' PEC will increase from 4.85 exajoule in 2023 to 5.73 exajoule in 2035. In other words, South Africa will experience an increase rate of 18.14% as compared to their total PEC in 2023. The forecasting results regarding the PECs of the BRICS countries, appear to be mostly in line with the associated nations' energy projections. Here are some examples from previous researches and scenarios, including *Accelerated*, *Net Zero* and *New Momentum*, which examine some potential routes for the world energy system. Brazil's PEC will increase to an average of around 14-16 exajoule towards 2050 as similar to the forecast in this study. These scenarios also forecast that China's PEC will rise, albeit in the short term, before falling over the next decade, while a strong increase for India's PEC (BP, 2023a; BP, 2023b; BP, 2023c). In South Africa, coal accounts for most of the PEC on the basis of its recent consumption values. It is possible to say that these figures are an indication which the coal-based total PEC of South Africa may increase in the coming years. This projection is supported by Hartono et al. (2021) since they said that under both pessimistic and optimistic scenarios, total PEC based on coal is anticipated to rise over time. As stated by Islam et al. (2022), the increasing demand for energy is highly associated with the growing population that live in cities. Therefore, it is conceivable that energy usage would rise in the coming years when considering the increases in the total and urban population ratios.

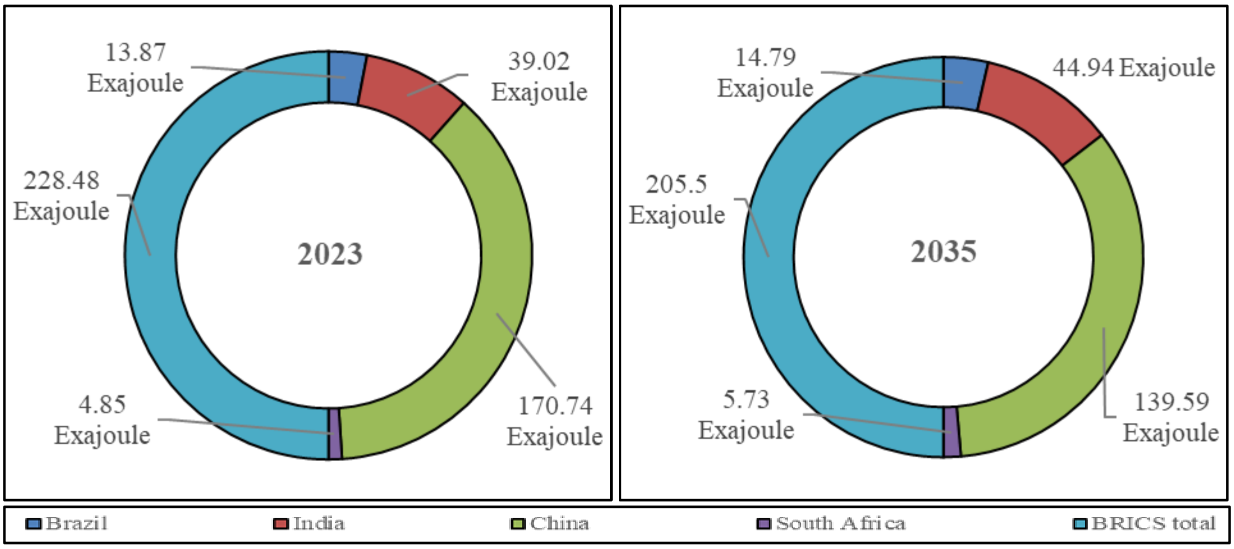


Figure 6. Total PECs of the BRICS economies in 2023 and 2035

6. Conclusions

This paper intends to derive and propose trend analysis-based forecast models for projecting the PECs of the BRICS countries. Basic conclusions are as follows. Firstly, it was found that the proposed models are based on the linear function for Brazil and inverse function for South Africa, while those are explained as power functions for India and China. Secondly, the verification and robustness tests of the proposed models showed that the proposed models have the potential to be useful in projecting future PECs in the associated countries, confirming that the TA is one of the effective useful tools for modelling and forecasting studies. Thirdly, the forecasted results demonstrated that there will be a decrease for the future PECs of the BRICS nations. Among the related emerging economics, it was disclosed that Brazil is projected to see the minimal growth, while South Africa is the only country that will experience the largest increase in PECs towards 2035. Due to their exceptional strong features, it was finally concluded that the BRICS countries will be able to steer the global economy in the near future.

7. Recommendations

This study has adopted only the BRICS countries. In order to generalization the results in future, studies can be conducted for other developed and emerging/developing countries as well. Similarly, the current research has only considered the population as the independent variable. Other relevant variables that affect the PECs such as urban population and gross domestic products, especially, for the BRICS countries, may be adopted and forecast models can be derived by the proposed approach. Additionally, unforeseen occurrences such as the COVID-19 pandemic and the conflict between the Russian Federation and Ukraine could pose serious obstacles to precisely projecting the PECs. This could result in several missing data points and poor data quality in the PEC databases, which would make accurate prediction difficult. Therefore, further study, re-evaluation and re-scenarisation of such events will be required. Conclusively, it is strongly suggested that the improvements in the PECs forecasts method should be carefully pursued for the indispensable contribution to the related nations' growth.

Conflict of Interest

The authors of the article declare that they have no conflict of interest.

Authors' Contribution

All authors planned and designed the study in addition to the data collection and analysis. Additionally, all authors commented on, read and approved the final version of the paper.

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