Chapter

Energy Policy Decision in the Light of Energy Consumption Forecast by 2030 in Zimbabwe

Remember Samu, Samuel Asumadu Sarkodie,
Murat Fahrioglu and Festus Victor Bekun

Abstract

Sustainable energy, environmental protection, and global warming are the most discussed topics in today's world. Demand forecasting is paramount for the design of energy generation systems to meet the increasing energy demand. In this chapter, an examination of the causal nexus between energy consumption, total population, greenhouse gas emissions, and per capita GDP was carried out to forecast Zimbabwe's energy consumption by 2030. A time series data from 1980 to 2012 were employed alongside econometric techniques to explore the causal relationship among the variables under review. The stationary test revealed the integration of all the data series of interest of order one $\sim$ I(1). The autoregressive integrated moving average (ARIMA) model forecasted Zimbabwe's 2030 energy demand around 0.183 quadrillion Btu as against the current 0.174 quadrillion Btu. The empirical finding is indicative for policy- and decision makers who design the energy policy framework geared towards achieving the universal access to modern energy technologies in Zimbabwe.

Keywords: energy demand, energy policy, forecasting, greenhouse gas emissions, ARIMA, Zimbabwe

1. Introduction

The mitigation of global warming, climate change, and environmental pollution (especially greenhouse gas emissions) has been in the mainstream discussions among environmental specialist and practitioners globally. Toxic greenhouse gas emissions, especially carbon dioxide that constitutes a larger percentage of atmospheric emissions, have a long-term effect on climate change. Agricultural activities, both on large and small scales; the generation, transmission, distribution, and consumption of energy; and many other human-influenced activities have been reported to be the major causes of high carbon dioxide emissions globally. Zimbabwe has suffered a rapid increase in energy demand mainly due to economic growth and population growth. There has been an insufficient supply of electrical energy—as of 2014, $\sim$7.25 million out of 14.6 million [1], representing 50% of Zimbabwe's population which lacked access to basic electrical energy and its related services. The deficit in electrical energy demand saw Zimbabwe importing almost 35% of its demand [2, 3]. The consumption rate has been growing rapidly, and the current

generation technologies are unable to meet this increasing demand. Based on the available fact, there is an urgent need to exhaust all the possible electricity generation technologies to achieve 100% connectivity.

Due to the relationship between human development and access to energy, Zimbabwe is currently categorized among the countries with low human development (i.e. an index of 0.49) [4]. With a very low life expectancy at birth of 33.5 years as of 2002, Zimbabwe has a low GDP per capita of US$ 2400 [4] and 0.92 metric tonnes as a value for the carbon dioxide emissions per capita [5].

It is of paramount importance that an investigation is done to ascertain the causal nexus between population, greenhouse gas emissions, energy consumption, and GDP per capita and forecast Zimbabwe's energy use by 2030. The energy demand is highly driven by energy intensity (I), gross domestic product per capita (GDPC), and total population (P). The total population is highly related to the development of social and cultural changes. The degree of development in the economy is reflected by the GDPC, while the energy intensity is related to the efficiency in the usage of energy by society [6].

In literature, a couple of noteworthy efforts on energy demand forecasting have been made. Neural networks, regression models, Box-Jenkins models, and econometric models are the most frequently applied techniques for energy forecasting [7]. The constraints and applications of economic models were outlined by Finniza and Baker in which they reviewed the alternative models and their applications for strategic decisions, investment alternatives, and environment analysis [8].

An autoregressive integrated moving average (ARIMA) and spatial ARIMA (ARIMASp) models are essential for forecasting environmental and non-environmental-related variables. These projections include forecasts of electrical energy demand and consumption, greenhouse gas emissions, economic growth, and day-ahead forecast of electricity prices [9–13].

Demand forecasts can be categorized into short-, medium-, or long-term depending mostly on the time frame of the forecast. The short-term demand forecasts vary depending on what variable is under investigation—from an hour-ahead, a day-ahead, to week-ahead projections [13]. Short-term demand forecasting is important for the economic cooperation and reliability of the power systems using linear models [14]. A month-ahead forecasting can be categorized into medium-term demand forecasting. Ref. [15] did a month-ahead demand forecasting for Spain using two neural networks and concluded that the results were better than those obtained using ARIMA models.

Demand forecasting can be in small, medium, or large location size. Ref. [16] did a campus and a building electricity demand forecasting using different regression models and compared the results from these models. In their conclusions, they deduced that almost all the models performed well in the overall campus than load forecasting of a single building.

There has been an extensive analysis of the causal nexus between energy consumption and economic growth. In the seminal study of Kraft and Kraft [17], on the relationship between energy use and gross national product using cointegration test and Granger causality techniques, the empirical finding was inconclusive for that prevailing study. The same study of Kraft and Kraft [17] was an invitation to numerous studies in the energy consumption analyses as outlined in a variety of studies [18–20]. However, the energy literature can be broadly classified into three groups, namely, (a) the energy-led growth hypothesis [21, 22], which implies that energy drives economic growth, (b) feedback hypothesis that infers that economic growth stimulates energy consumption and vice versa, [23–25] and finally (c) the neutrality hypothesis [26–28], in which there is a strong assumption that energy has little or no impact on economic growth. However, there are very limited and

sporadic literature documented regarding forecasting energy demand for sub-Saharan Africa (SSA) especially Zimbabwe—which is one of the fastest-growing economies in southern Africa.

As of recent, there are studies which include the empirical study by Sarkodie and Owusu [29] on carbon dioxide emissions, economic growth, energy use, and population interaction in a multivariate and causality framework, for the case of Ghana from 1971 to 2013. In this study, their empirical result revealed a cointegration relationship among all the series based on the vector error correction model (VECM) and autoregressive distributive lag model (ARDL). Their study validated the energy-induced growth hypothesis and the feedback hypothesis.

Furthermore, studies on energy forecasting in Spain precisely Asturias conducted by [30] utilized a univariate ARIMA Box-Jenkins approach from 1980 to 1996. Their study unraveled an optimum forecast with minimal forecast error. Similarly, for the case of Ghana, Sarkodie [31] estimated the electricity consumption by 2030 via an ARIMA technique. Sarkodie's [31] empirical study submitted that Ghana energy consumption will increase from 8.52 billion kWh to 9.52 billion kWh in 2030. Sarkodie's [31] findings were indicative of policymakers, which inform investments in energy infrastructure. The study also recommended the increase in energy generation to match the projected demand. In addition, Sarkodie and Owusu [32] investigated Nigeria energy use via forecast by 2030 using an ARIMA and ETS approach from 1971 to 2030. The empirical evidence showed that a 1% increase in energy use had a direct impact on carbon dioxide emissions by 3%. The ARIMA forecast prediction showed that energy use will increase from 975 kg in 2012 to 915 kg per oil equivalent by 2030.

In this chapter, a linear regression analysis is employed for the examination of the causal relationship between the variables under study. A time series data from 1980 to 2012 acquired from *World Data Atlas* [33] were used. Statistical forecasting models are then employed to project Zimbabwe's energy use by 2030. Most importantly this chapter will give information on energy policies, planning, and management of environmental pollution in order to minimize the effects of climate change and forecast Zimbabwe's energy demand and reduce the energy deficit the country is currently facing.

This chapter is of paramount importance to Zimbabwe, as it will increase the awareness of sustainable development and serve as a reference tool for integrating climate change measures into energy policies, practices, and planning by the government. Based on the findings of this chapter, Zimbabwe may be able to model an energy mix that will ensure 100% energy availability to all stakeholders. Zimbabwe is not utilizing its renewable energy resources on a large scale [2, 3]. This chapter will provide insights into how policymakers can incorporate the vast resources into the energy portfolio to ensure increased connectivity by the year 2030. Section 2 of the chapter briefly describes the methodology employed and the materials used. Results and discussion are outlined in Section 3 of the chapter. Section 4 presents the conclusions from the study, the energy policy implications, and possible recommendations for future studies.

2. Methodology

2.1 Data

The dataset employed in this present study consists of macroeconomic variables. Seven macroeconomic variables recorded yearly from 1980 to 2012 were analyzed. The data were retrieved from *World Data Atlas* [34]. These variables were then

used to econometrically forecast the energy demand of Zimbabwe up to the year 2030. Time series data on total greenhouse gas emissions (kt of CO_2 equivalent), total carbon dioxide emissions (kt), total population (million), GDP per capita (2010US$), total primary energy production (quadrillion Btu), total primary energy consumption (Quadrillion Btu), and total electricity net generation (Billion kW hours) were employed. The data utilized spans from 1980 to 2012. As a preprocessing technique, missing values were imputed using MICE package in R software. Linear regression analysis was then employed to examine the causal relationship between these variables under investigation.

2.2 Model specification

The functional relationship among total greenhouse emission, total carbon dioxide emission, total population, per capita GDP, total energy production, total primary energy consumption, and total electricity net generation is based on the works of Reference [31, 32, 35]. The functional forms can be represented as follows:

Model A: ln TPEC = f (lnTGHC, lnTENG, lnTCO$_2$, lnTPOP, lnPGDP, lnTPEP).

Model A will help us ascertain the impact of total energy consumption on other explanatory variables:

$$\ln TPEC_t = \alpha + \beta_1 \ln TGHC + \beta_2 \ln TENG + \beta_3 \ln TCO_2 + \beta_4 \ln TPOP$$
$$+ \beta_5 \ln PGDP + \beta_6 \ln TPEP + \varepsilon_t \tag{1}$$

while model B seeks to verify the extent of CO_2 emission on economic growth and the impact of population growth.

Model B: lnTCO$_2$ = f (lnPGDP, lnTPOP, lnTENG, lnTGHC, lnTPEC, lnTPEP).

$$\ln TCO_2 = \alpha + \beta_1 \ln PGDP + \beta_2 \ln TPOP + \beta_3 \ln TENG + \beta_4 \ln TGHC$$
$$+ \beta_5 \ln TPEC + \beta_6 \ln TPEP + \varepsilon_t \tag{2}$$

where t is time trend, also $\alpha, \beta_1, \beta_2....\beta_6$ are unknown coefficients of repressors, and ε_t is the stochastic error term for the formulated models.

The empirical route of this study proceeds as follows: first, determination of the order of integration of series; second, estimation of the ordinary least squares (OLS) regression; and lastly, the forecast estimation.

2.3 Model estimation

Based on relevant studies [31, 32, 36] and our long-term forecasting using macro variables, an autoregressive integrated moving average (ARIMA) and spatial ARIMA (ARIMASp) models were utilized. These models are useful in forecasting greenhouse gas emissions, economic growth and electrical energy demand, consumption, and electricity prices [9, 10, 12, 32]. Some studies have utilized neural networks for a medium-term demand forecasting and concluded that the results were better than those obtained using ARIMA models [15]. Based on further analysis of the data variables and available literature and resources, a suitable model will be chosen for the continuation of this study. The ARIMA model [ARIMA (p. d, q)] was conducted in this chapter given as

$$\varphi(B)\nabla^d z_t = \phi(B)\alpha_t \, or \, Z_t = \sum_{i=0}^{p} \gamma Z_{t-1} + \alpha_t - \sum_{k=1}^{q} \gamma_i \alpha_{t-k} \qquad (3)$$

where

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 ... - \varphi_k B^k \qquad (4)$$

3. Results and discussions

3.1 Descriptive statistical analysis

This section outlines the descriptive statistical analysis of the study variables. **Figure 1** displays the trend of the variables after data imputation. It is visible from the trend that population increases rapidly, while the trend of GDP, total greenhouse gas, and carbon dioxide emissions exhibits similar feature, but fluctuations are observed in the trend of energy consumption.

Table 1 presents a summary of the descriptive statistical analysis of the study variables. Further analysis of the parameters indicates that total population and energy generation has long left tails (negative skewness), while CO_2 emissions, GDP, and energy consumption have long right tails (positive skewness). Total primary energy production and total greenhouse gas emission exhibit a positive skewness. Furthermore, energy production shows a leptokurtic distribution since its excess kurtosis is greater than zero, while the rest of the variables have an excess kurtosis less than zero, thus presenting a platykurtic distribution.

Grubbs' test was then used to estimate outliers in the study variables. Evidence from **Table 2** reveals the highest values of all the variables, except total population,
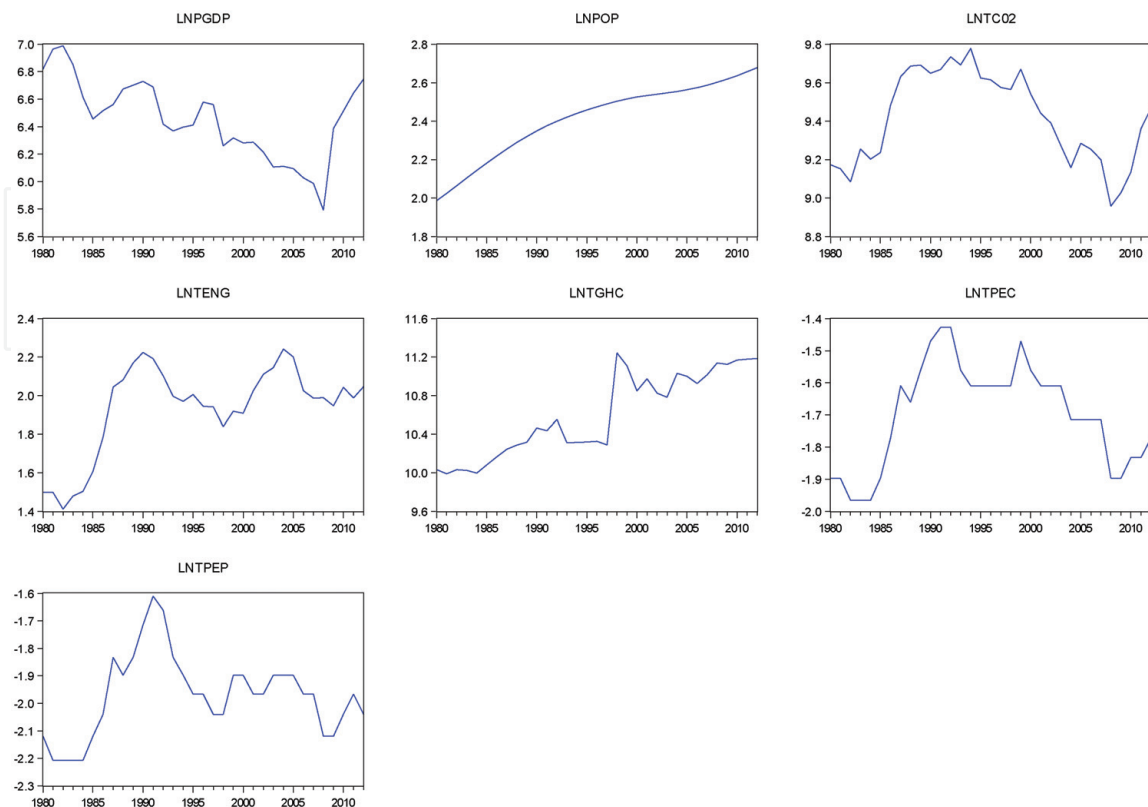

Figure 1.
Plot of series in natural logarithm.

	LNPGDP	LNPOP	LNTCO$_2$	LNTENG	LNTGHC	LNTPEC	LNTPEP
Mean	6.457	2.413	9.414	1.936	10.599	−1.699	−1.971
Median	6.455	2.475	9.441	1.989	10.466	−1.661	−1.966
Maximum	6.989	2.679	9.778	2.242	11.244	−1.427	−1.609
Minimum	5.791	1.987	8.958	1.411	9.991	−1.966	−2.207
Std. dev.	0.289	0.195	0.238	0.234	0.436	0.162	0.151
Skewness	−0.208	−0.722	−0.160	−0.980	0.075	−0.166	0.341
Kurtosis	2.524	2.407	1.696	2.913	1.450	1.946	2.921
Jarque-Bera	0.549	3.352	2.481	5.288	3.333	1.678	0.646
Probability	0.760	0.187	0.289	0.071	0.189	0.432	0.724
Sum	213.073	79.641	310.662	63.873	349.764	−56.073	−65.037
Sum sq. dev.	2.671	1.219	1.806	1.754	6.078	0.842	0.725
Observations	33	33	33	33	33	33	33

Table 1.
Summary statistics.

Variable	G	U	P-value	Alternative hypothesis
GDP	2.0	0.9	0.4	Highest value 1084.21 is an outlier
Population	2.0	0.9	1	Lowest value 5.39 is an outlier
CO$_2$ emissions	2.0	0.9	1	Highest value 17645.6 is an outlier
GHG emissions	2.0	0.9	1	Highest value 76391.8 is an outlier
Energy production	3.0	0.8	0.1	Highest value 0.2 is an outlier
Energy consumption	2.0	0.9	0.9	Highest value 0.24 is an outlier
Energy generation	2.0	0.9	1	Highest value 9.41 is an outlier

Table 2.
The Grubbs test for outliers.

are outliers. The Anderson-Darling test was done to test for the normality of the data variables. Testing at a 5% significance level, the null hypothesis is rejected if the p-value is less than or equal to 5%; hence, it can be concluded that the data do not follow a normal distribution. However, if the p-value is greater than 5%, then the test fails to reject the null hypothesis of normal distribution.

Table 3 presents the correlation matrix that exists between the variables.

The results of the correlation coefficient estimation show a positive significant relationship between per capita GDP and the total population. Thus, this implies that a higher population increases national income for the study country. Similarly, negative association but significant relationship exists among PGDP and TENG as well as TPEC but insignificant for TPEC and PGDP. This revelation implies that energy intensity impedes economic growth at certain threshold validating the environmental Kuznets curve hypothesis (EKC).

3.2 Anderson-Darling normality test

Table 4 shows that except GDP with a p-value greater than 5%, the entire variables do not follow a normal distribution. It is therefore evident that we fail

	LNPGDP	LNPOP	LNTCO$_2$	LNTENG	LNTGHC	LNTPEC	LNTPEP
LNPGDP	1						
t-stat	—						
P-value	—						
No. obs.	33						
LNPOP	−0.667	1					
t-stat	−4.987	—					
P-value	0.00	—					
No. obs.	33	33					
LNTCO$_2$	0.158	0.045	1				
t-stat	0.893	0.250	—				
P-value	0.379	0.8039	—				
No. obs.	33	33	33				
LNTENG	−0.486	0.721	0.404	1			
t-stat	−3.095	5.788	2.459	—			
P-value	0.004	0.000	0.020	—			
No. obs.	33	33	33	33			
LNTGHC	−0.635	0.886	−0.177	0.550	1		
t-stat	−4.578	10.642	−0.999	3.665	—		
P-value	0.0001	0	0.3255	0.0009	—		
No. obs.	33	33	33	33	33		
LNTPEC	−0.217	0.336	0.823	0.697	0.163	1	
t-stat	−1.238	1.987	8.077	5.415	0.917	—	
P-value	0.225	0.056	0.000	0.000	0.366		
No. obs.	33	33	33	33	33	33	
LNTPEP	−0.186	0.314	0.700	0.787	0.164	0.890	1
t-stat	−1.055	1.843	5.451	7.103	0.925	10.878	—
P-value	0.299	0.075	0.000	0.000	0.362	0.000	
No. obs.	33	33	33	33	33	33	33

Note: Table reports the estimates of the Pearson correlation coefficient between the pairs of variables. t-stat is the t-statistics for the significance of the correlation coefficient, and p-value is its marginal probability.

Table 3.
Correlation coefficient estimates.

to reject the null hypothesis for GDP. Further analysis of the GDP distribution from the fitting is shown in **Figure 2**, while the Cullen and Frey graph in **Figure 3** concludes that the data for GDP follows a normal distribution. The remaining distributions of the variables were decided using Cullen and Frey graph.

Further evidence from the Cullen and Frey graph support the previous evidence that these variables do not follow a normal distribution. The PDF plots presented in **Figures 4** and **5** additionally support that GDP follows a normal distribution. Energy consumption was used in this chapter as a dependent variable for the forecasting. The relationship between energy consumption and population shown

Variable	A	P-value
GDP	0.2	0.9000
Population	0.9	0.0300
CO_2 emissions	2	0.0004
GHG emissions	3	0.0000
Energy production	1	0.0020
Energy consumption	2	0.0003
Energy generation	2	0.0001

Table 4.
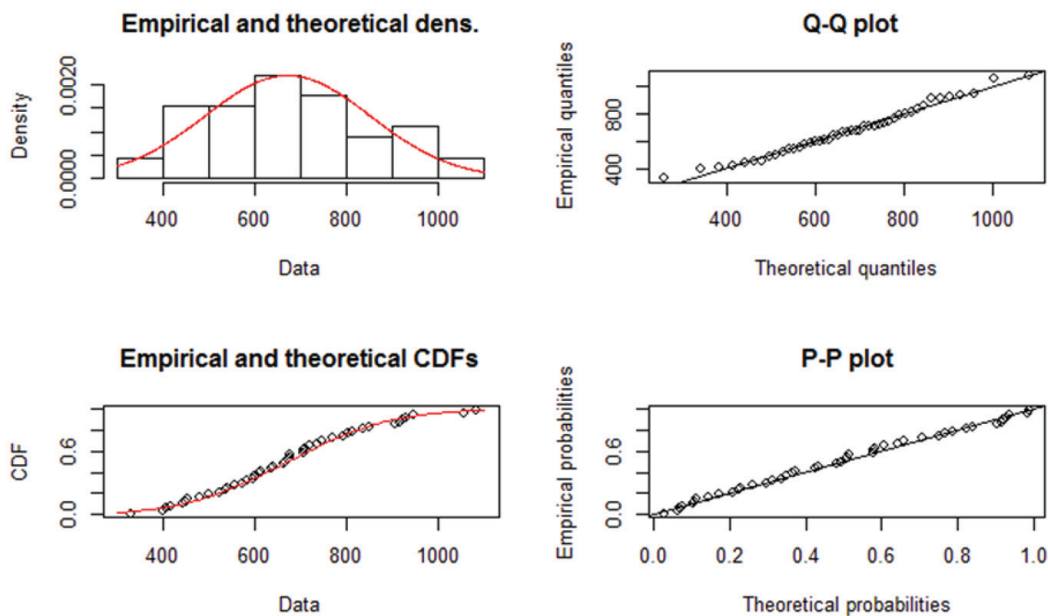*Anderson-Darling normality test.*

Figure 2.
Normal distribution fitting for GDP.
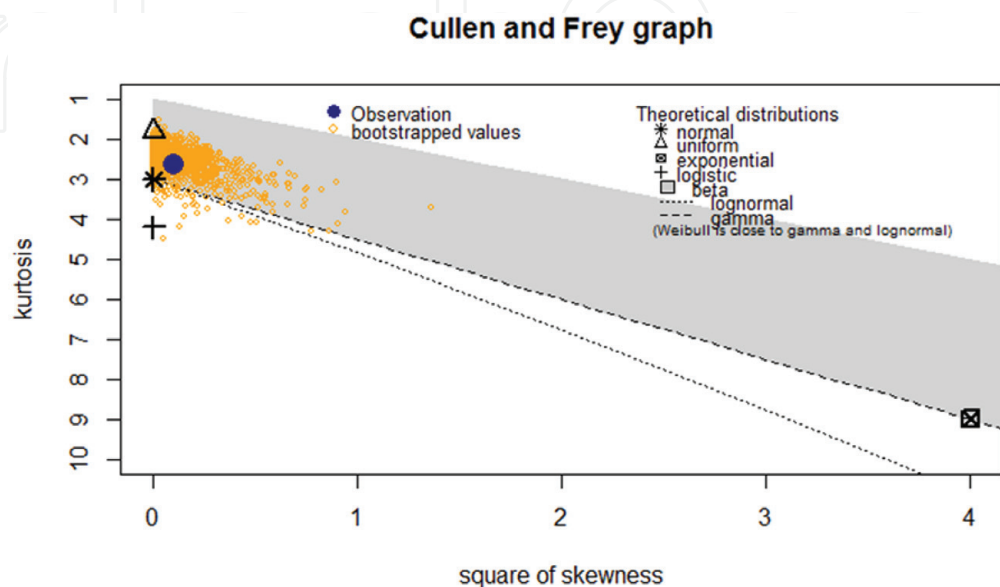
Figure 3.
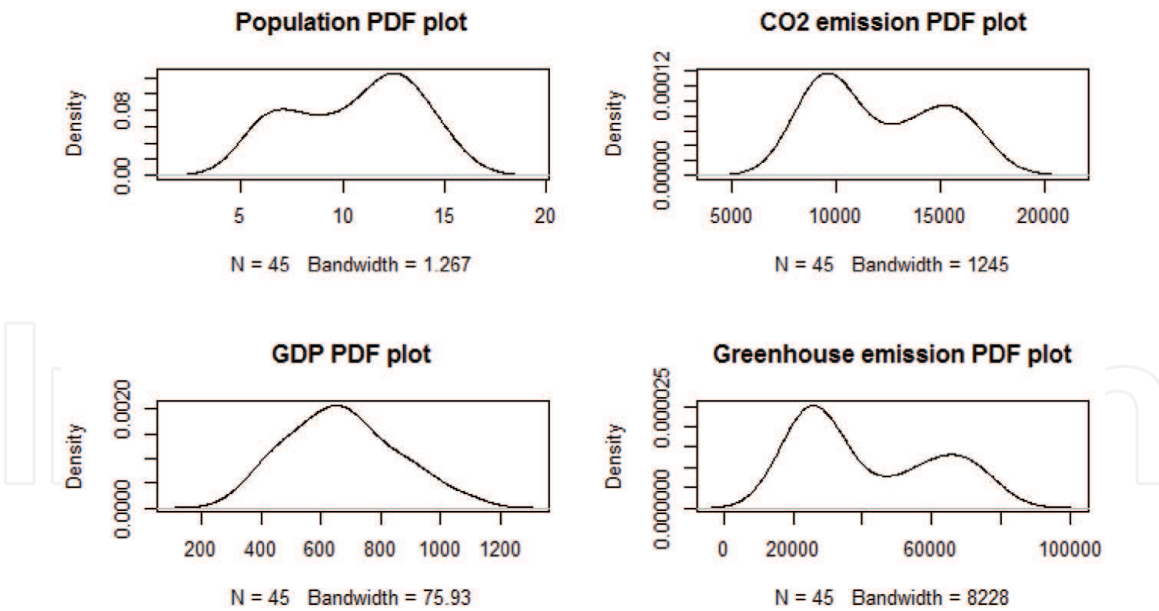*GDP fits normal, lognormal, gamma, and beta distributions.*
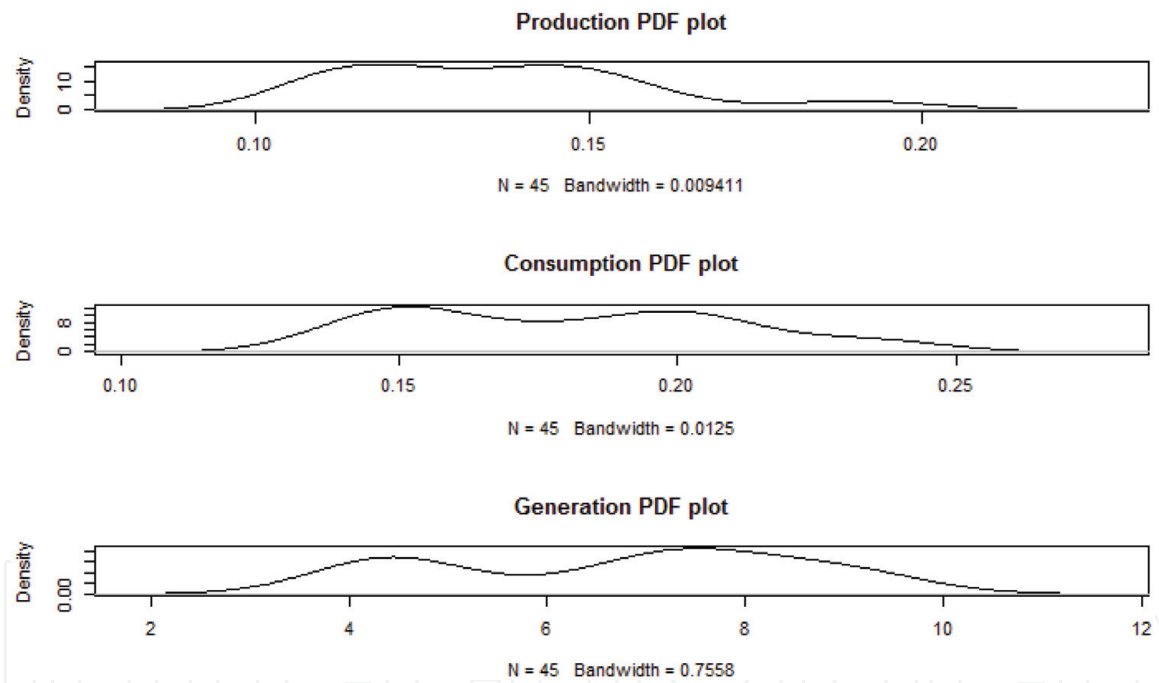
Figure 4.
PDF plots for the study variables (a).

Figure 5.
PDF plots for the study variables (b).

in **Figure 6** reveals that energy consumption increases with an increase in population.

3.3 Stationarity test

It is well established that most macroeconomic variables possess trends/seasonality; thus, the need to know the order of integration of such series is pertinent to avoid spurious regression and misleading policy implication. This current chapter employed augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root test to ascertain the stability traits and asymptotic properties of the variables under consideration. These tests are conducted with the null hypothesis of a unit root
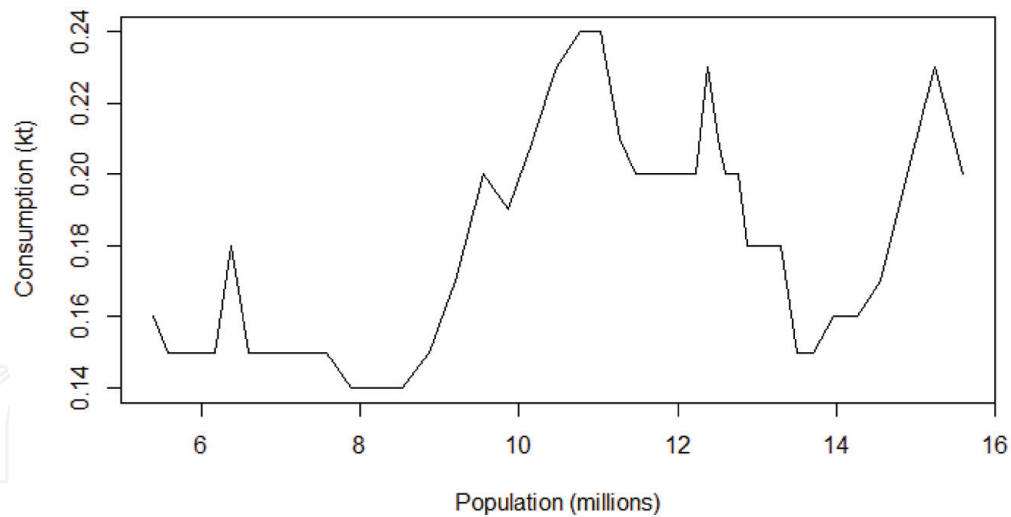
Figure 6.
A relation between energy consumption and total population.

Variables	Level				First difference			
	ADF		PP		ADF		PP	
	τ_μ	τ_T	τ_μ	τ_T	τ_μ	τ_T	τ_μ	τ_T
LNGDPC	−2.01	−2.08	−2.19	−3.18	−5.21***	−5.14***	−5.09***	−5.17***
LNTCO$_2$	−1.69	−0.67	−6.23	−6.17	−6.23***	−4.19***	−6.18***	−6.18***
LNTGHC	0.99	−3.63	−7.55	−7.47	−0.99**	−8.20**	3.64**	−8.14***
LNTPOP	−2.50	−3.10	−2.18	−3.08	−3.68**	−1.29**	1.17***	1.11***
LNTPEP	−2.45	−3.72	−3.64	−3.82	1.72***	1.73***	−4.63***	−4.65***
LNTPEC	−1.57	−1.42	−4.57	−4.67	−1.69***	−1.41**	−4.57***	−4.62***
LNTENG	−3.79	−3.61	−3.74	−3.81	−1.99***	1.76***	−6.18***	−6.23***

Note: τ_μ represents a model with intercept, while τ_T denotes model with intercept and trend.
**Significant at 5% level.
***Significant at 1% level.

Table 5.
Unit root results.

against the alternative of stationarity [37, 38]. **Table 5** presents the unit root test.
The general form of the unit root test is given as

$$\Delta Y_t = \beta_1 + \beta_2 t + \gamma Y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} + \in_t \qquad (5)$$

where $\in_t$ denotes the Gaussian white noise term which is asymptotically characterized by zero mean and constant variance. The null hypothesis of the unit root test is nonstationary against the alternative of stationarity.

The unit root test reported in **Table 5** reveals that all series are integrated of order one $\sim I\,(1)$, that is, it has a unit root. However, all variables turn stationary at first difference, thus integrated of order one $\sim (1)$. Subsequently, this study proceeded with the ordinary least squares (OLS) estimation.

Tables 6 and **7** present the OLS regression estimates for models A and B, respectively. **Table 6** shows a tradeoff between total population and total primary consumption. That is, a 1% increase in the total population decreases the total

Variable	Coefficient	Std. error	t-statistic	Prob.
C	−3.7982	1.1311	−3.3580	0.0024
LNTGHC	0.0489	0.0555	0.8803	0.3868
LNTENG	−0.0245	0.1185	−0.2071	0.8376
LNTCO$_2$	0.3689	0.0705	5.2314	0.0000
LNPOP	−0.0486	0.1586	−0.3065	0.7617
LNPGDP	−0.1020	0.0473	−2.1592	0.0402
LNTPEP	0.5421	0.1672	3.2420	0.0032
R-squared	0.9091			
F-statistic	43.3549			
Prob (F-statistic)	0.0000			

Model A: lnTPEC = f(lnTGHC, lnTENG, lnTCO$_2$, lnPOP, lnPGDP, lnTPEP).

Table 6.
Regression estimation for Model A.

Variable	Coefficient	Std. error	t-statistic	Prob.
C	11.7740	1.2570	9.3668	0.0000
LNPGDP	0.2396	0.0878	2.7282	0.0113
LNPOP	0.5429	0.2895	1.8754	0.0720
LNTENG	−0.1941	0.2270	−0.8551	0.4003
LNTGHC	−0.2367	0.0991	−2.3897	0.0244
LNTPEC	1.3901	0.2657	5.2314	0.0000
LNTPEP	−0.0148	0.3846	−0.0386	0.9695
R-squared	0.8404			
F-statistic	22.8174			
Prob (F-statistic)	0.0000			

Model B: lnTCO$_2$ = f(lnPGDP, lnTPOP, lnTENG, lnTGHC, lnTPEC, lnTPEP).

Table 7.
Regression estimation for Model B.

energy consumption by 0.05%. Similarly, a negative trend was seen among per capita GDP total energy consumption with a magnitude of 0.10%. Thus, we can infer that population does not increase CO_2 emission in Zimbabwe. However, a positive and significant relationship is observed among TPEP and TGHC with the dependent variable at a magnitude of 0.54 and 0.05%. The fitted model has a robust coefficient of determination (R^2) of 90%, implying that 90% of the variation in total primary energy consumption was explained by the explanatory variables, while the rest 10% are left uncaptured in this model. The joint significance of the model by the F-statistic was also significant at all levels (1, 5, and 10%). In the same way, **Table 7** targeted for model B. The model has a coefficient of 84%. That is, 84% of the variation in CO_2 was explained by another explanatory variable with F-statistic significance indicating joint significance among all variables. Interestingly, the fitted model shows that a 1% increase in PGDP increases CO_2 by 0.24%. Similarly, there is also a positive trend between CO_2 and TPOP with over 0.54%.

Year	TPECF (predicted)	TPEC
1980		0.15
1981		0.15
1982	0.151	0.14
1983	0.151	0.14
1984	0.152	0.14
1985	0.153	0.15
1986	0.153	0.17
1987	0.154	0.2
1988	0.155	0.19
1989	0.155	0.21
1990	0.156	0.23
1991	0.157	0.24
1992	0.157	0.24
1993	0.158	0.21
1994	0.159	0.2
1995	0.159	0.2
1996	0.160	0.2
1997	0.161	0.2
1998	0.161	0.2
1999	0.162	0.23
2000	0.163	0.21
2001	0.163	0.2
2002	0.164	0.2
2003	0.165	0.2
2004	0.165	0.18
2005	0.166	0.18
2006	0.167	0.18
2007	0.167	0.18
2008	0.168	0.15
2009	0.169	0.15
2010	0.169	0.16
2011	0.170	0.16
2012	0.171	0.17
2013	0.171	
2014	0.172	
2015	0.173	
2016	0.173	
2017	0.174	
2018	0.175	
2019	0.175	

Year	TPECF (predicted)	TPEC
2020	0.176	
2021	0.177	
2022	0.177	
2023	0.178	
2024	0.179	
2025	0.179	
2026	0.180	
2027	0.181	
2028	0.181	
2029	0.182	
2030	0.183	

Table 8.
Forecast (ARIMA) for total energy consumption.
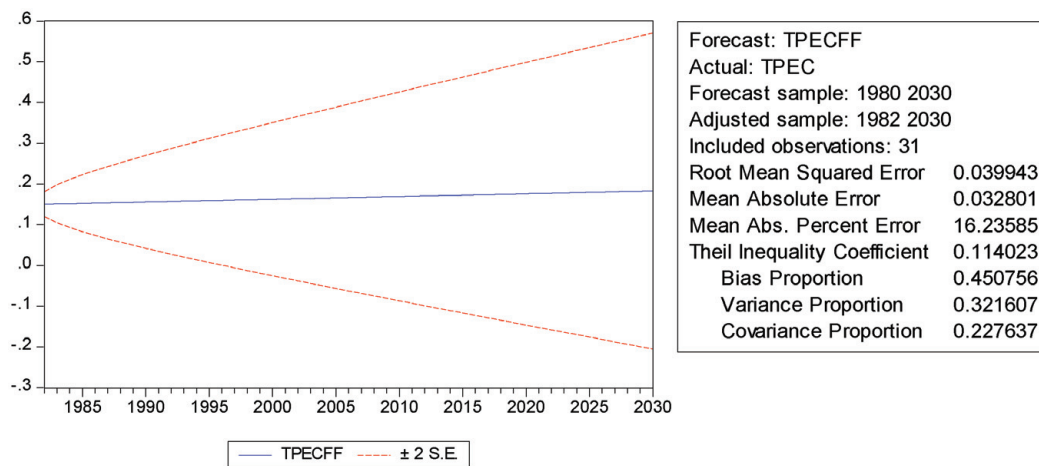
Figure 7.
ARIMA forecast for Zimbabwe electricity consumption.

Table 8 reports the ARIMA (1,1,1) which is the best fit and parsimonious model for the choice regression fit. For brevity, other simulations and OLS regression can be made available on request as well as a forecast for other energy-related variables. The study mainly focuses on energy demand forecast. The estimation for the forecast reveals that electricity consumption for Zimbabwe as reported in **Table 5** was conducted utilizing the dataset from 1980 to 2012 after the imputation of missing data in order to avoid spurious estimation. Empirical evidence shows that in 2030 energy consumption will reach ∼0.18 quadrillion Btu against the currently available ∼0.17 quadrillion Btu.

The estimation affirms the goodness of fit with a coefficient of determination R^2 of over 80%, with a corresponding F-statistic rejected at $p < 0.01$—indicating joint significant of the selected model. Finally, the study forecast also displays high parsimony with harmony among the root mean square error (RSME) of ∼0.04, while the mean absolute error was ∼0.03. Similarly, the Theil inequality coefficient was ∼0.11.

Figure 7 reports the diagrammatic view with relatively fair deviation from the forecast variable. All forecast indicators resonate with **Figure 7**.

4. Conclusion and policy implications

This study employed econometric techniques to forecast Zimbabwe's energy consumption by 2030. Using the rule of thumb (i.e. less than 20% of the dataset), it was possible to impute the NA values in the dataset using MICE package in R. The unit root tests revealed that all the variables are integrated of order one—which informed our choice of ARIMA model. Using an ARIMA (1,1,1) model with data spanning from 1980 to 2012, the empirical analysis showed Zimbabwe's energy consumption by 2030 will increase to ~0.18 quadrillion Btu from ~0.17 quadrillion Btu in 2017. Thus, the need to diversify and intensify into clean energy sources is crucial among policymakers. This is in order to meet the energy demands given the dynamic fast-growing nature of the study area. The current energy policy in Zimbabwe is found to lack a large-scale utilization of solar and wind resources. Such policy suggests the following measures: encourage the generation of electricity from biomass cogeneration and mini-hydro projects and bagasse from sugar cane—Hippo Valley and Triangle sugar estates generate for their own consumption. However, the existing energy policy suggested the following strategies which have not been implemented: extension of Kariba south by the end of 2016 and 800 MW Batoka hydro by 2020 and mandate the installation of solar geysers by 2013 and fix (REFIT) renewable feed-in tariffs.

Zimbabwe's energy policy currently lacks research on energy consumption forecast; hence, this chapter is indicative for policymakers who design the energy policy framework. The OLS regression revealed a positive relationship between carbon dioxide emissions (CO_2), population (POP), and gross domestic product (GDP). Thus, it implies that population triggers economic growth; however, there is a negative deteriorating effect on environmental quality. It means that policymakers are enjoined to bring forth environmentally friendly regulations to combat the excesses of pollution. Such regulations include renewable energy policy that promotes large-scale utilization of renewable energy resources.

Conflict of interest

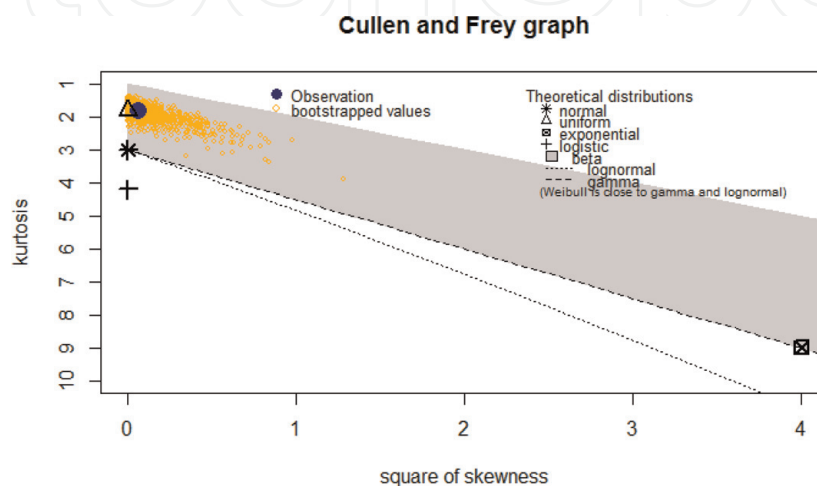Authors declare no conflict of interest.

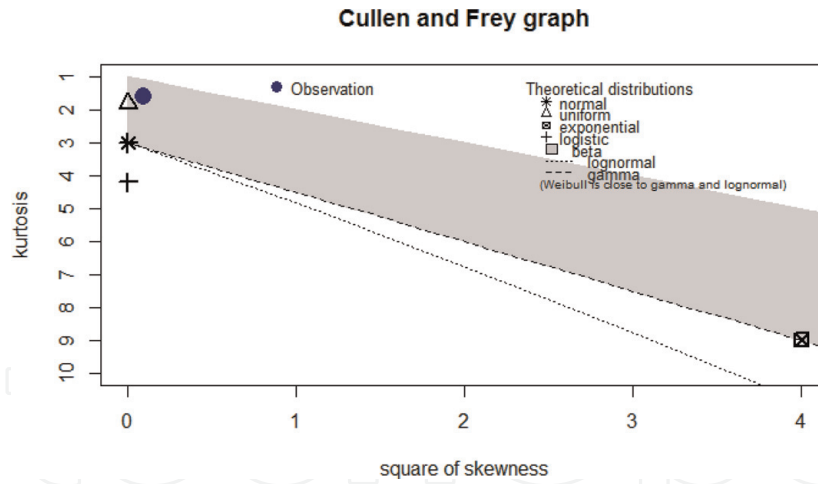## Appendix A

Figure 8.
Population follows a uniform distribution.

Figure 9.
CO_2 emissions follow uniform and beta distributions.
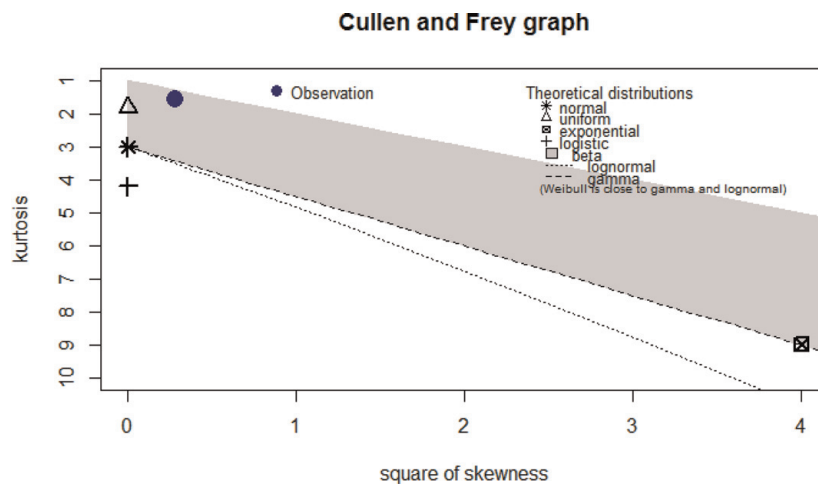

Figure 10.
GHG emissions follow a beta distribution.

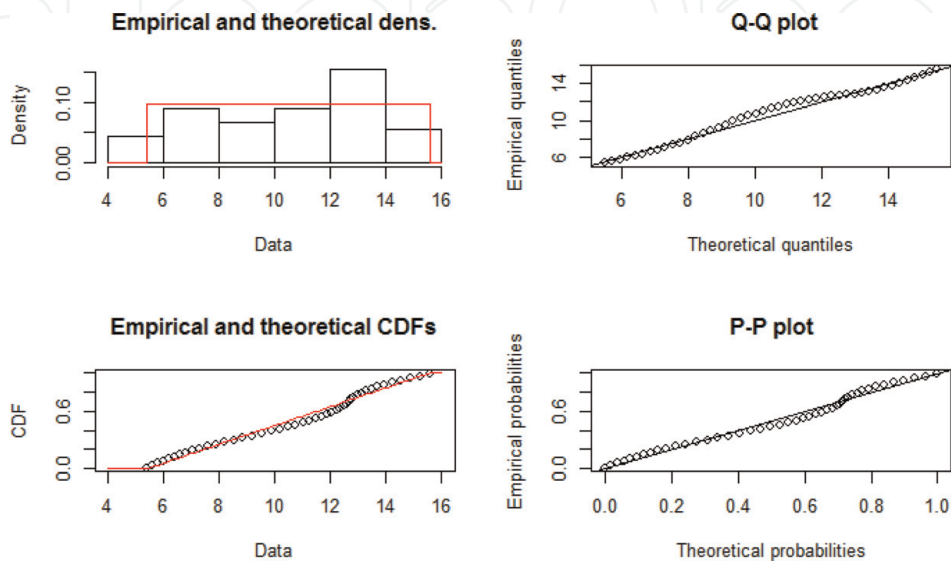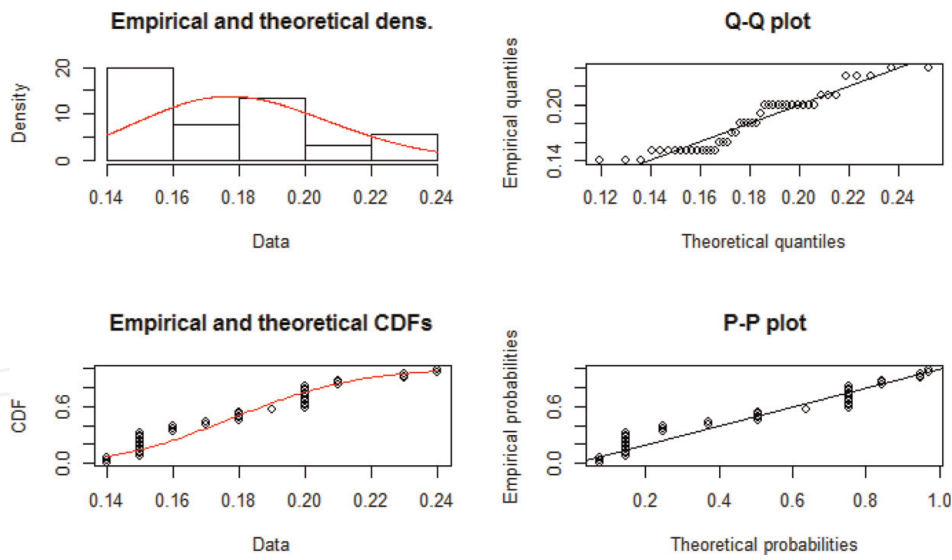## Appendix B

Figure 11.
Population distribution.
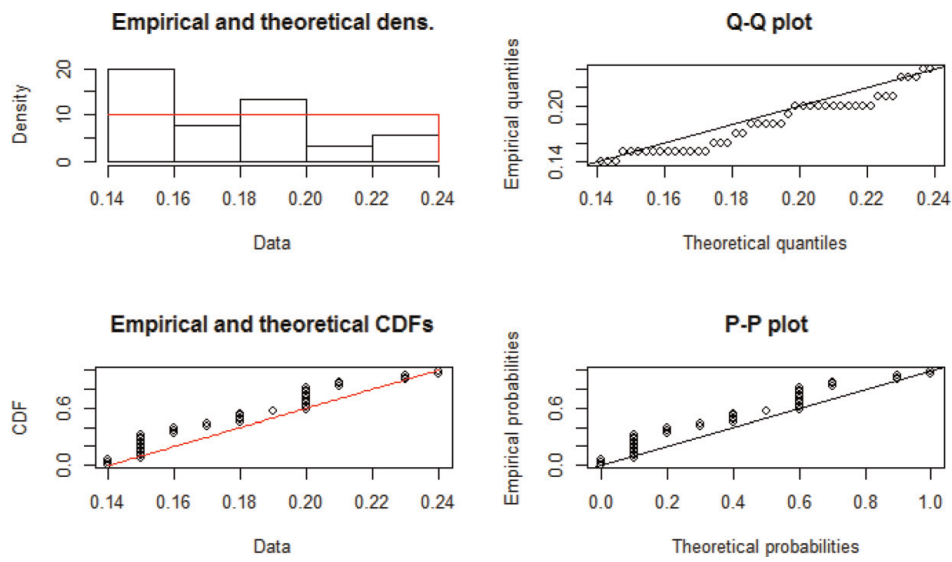
Figure 12.
Energy consumption distribution.
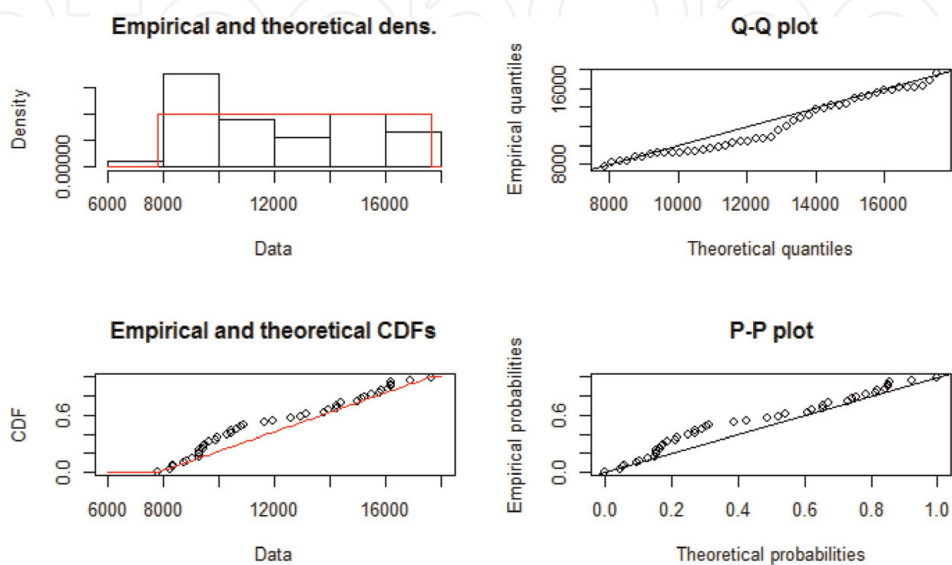

Figure 13.
Energy generation distribution.

Figure 14.
CO_2 emission distribution.

Author details

Remember Samu[1], Samuel Asumadu Sarkodie[2]*, Murat Fahrioglu[3]
and Festus Victor Bekun[4]

1 Discipline of Engineering and Energy, College of Science, Health, Engineering and
Education, Murdoch University, Murdoch, Australia

2 Nord University Business School (HHN), Bodø, Norway

3 Electrical and Electronics Engineering Department, Middle East Technical
University Northern Cyprus Campus, Mersin, Turkey

4 Department of Economics, Eastern Mediterranean University, Famagusta,
Northern Cyprus, Turkey

*Address all correspondence to: asumadusarkodiesamuel@yahoo.com

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