Adıyaman University Journal of Science
https://dergipark.org.tr/en/pub/adyujsci
DergiPark AKADEMİK
ISSN 2147-1630
e-ISSN 2146-586X

Assessing the Renewable Energy Efficiency Levels of BRICS Countries and Turkey Using Stochastic Frontier Analysis and Information Complexity Criteria

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Received: 19.06.2020 **Accepted:** 14.05.2021 **Published:** 30.06.2021

Abstract

Renewable energy is a sustainable energy source that can be produced repeatedly by using the resources that exist in nature's own evolution. Renewable energy sources occupy an important place in the world and our country due to their renewability, minimal environmental impact, low operating and maintenance costs, and their national qualifications, and reliable energy supply features. In this study renewable energy efficiency levels for the BRICS countries and Turkey were examined. In the study covering the period 2006-2015, we used the SFA method for efficiency analysis in input selection. We used information complexity criteria to decide which input set is the best on renewable energy efficiency process. The selection results pointed out to the CO_2 emission and Energy intensity as the most explanatory inputs. We observed that the selected inputs have significant effect on the renewable energy efficiencies. According to results, the renewable energy efficiency values follow approximately the same pattern for each country and do not vary significantly between the years. When comparing the renewable energy efficiencies among the countries, Brazil has the best performance with approximately 97% efficiency level, and Russia has the worst one. The efficiency level of Turkey is rather weak, but it is not the worst and the average efficiency is very close to China.

* Corresponding Author DOI: 10.37094/adyujsci.755048

Keywords: Renewable energy; Stochastic frontier analysis; Information complexity criteria; BRICS; Turkey.

BRICS Ülkelerinin ve Türkiye'nin Yenilenebilir Enerji Verimliliği Düzeylerinin Stokastik Sınır Analizi ve Bilgi Karmaşıklığı Kriterleri Kullanılarak Değerlendirilmesi

Öz

Yenilenebilir enerji, doğanın kendi evriminde var olan kaynaklar kullanılarak tekrar tekrar üretilebilen sürdürülebilir bir enerji kaynağıdır. Yenilenebilir enerji kaynakları, yenilenebilirlik, minimum çevresel etki, düşük işletme ve bakım maliyetleri, ulusal nitelikleri ve güvenilir enerji tedarik özellikleri nedeniyle dünyada ve ülkemizde önemli bir yer tutmaktadır. Bu çalışmada BRICS ülkeleri ve Türkiye için yenilenebilir enerji verimliliği düzeyleri incelenmiştir. 2006-2015 dönemini kapsayan çalışmada, girdi seçiminde verimlilik analizi için SFA yöntemini uygulandı. Yenilenebilir enerji verimliliği sürecinde hangi girdi setinin en iyi olduğuna karar vermek için bilgi karmaşıklığı kriterlerini kullandık. Seçim sonuçları CO_2 emisyonunu ve enerji yoğunluğunu en açıklayıcı girdiler olarak ortaya koymaktadır. Ayrıca seçilen girdilerin yenilenebilir enerji verimliliği üzerinde önemli etkisi olduğu gözlemlendi. Sonuçlara göre, yenilenebilir enerji verimliliği değerleri her ülke için yaklaşık olarak aynı kalıbı takip etmektedir ve yıllar arasında önemli bir farklılık göstermemektedir. Ülkeler arasında yenilenebilir enerji verimliliği karşılaştırıldığında, Brezilya yaklaşık %97 verimlilik seviyesi ile en iyi performansa sahiptir ve Rusya en kötü performansa sahiptir. Türkiye'nin verimlilik seviyesi oldukça zayıf olmakla birlikte en kötü değil ve ortalama verimlilik Çin'e çok yakındır.

Anahtar Kelimeler: Yenilenebilir enerji; Stokastik sınır analizi; Bilgi karmaşıklığı kriterleri; BRICS, Türkiye.

1. Introduction

Energy is an important factor for the social wealth and economic development of countries. Economic developments, the rapidly growing population, and the developing industry have further increased the energy requirement and energy use. Despite the fact that energy requirement is increasing, fossil sources of energy will be exhausted in the near future [1]. The irregular use of fossil fuels is a danger for our future as well as to the present. Unconsciously used of these fuels to meet the energy needs, ecological balance and global climate change cause disruption. Emissions that show up with consumption threaten the environment and human health.

With renewable energy, it is possible to meet increasing energy sources safely and cleanly. Renewable energy is the energy obtained from natural sources such as sun and wind, which can renew itself quickly after consumption and is not exhausted as it is used. Renewable energy sources are the ones that are renewed in a continual motion and are ready to be used in nature. Since these sources are not fossil-derived (coal, oil and carbon derivatives), and CO_2 emissions are generated at a low level when generating electrical energy, their impact and harm to the environment are much lower than that of conventional energy sources.

In order to meet the increasing energy demand, the studies on renewable energy sources and energy efficiency should be increased. Increasing energy efficiency is a worldwide problem and naturally depends heavily on energy use. High-income developing countries known as BRICS (Brazil, Russia, India, China and S. Africa) countries and Turkey are the leading countries in renewable energy sector investment. The performance measurement of renewable energy sources is as important as the investment and production of these resources. Some of the studies in the literature on energy efficiency are given below.

Song et al. [2] used a Super SBM model to measure and calculate the energy efficiency of BRICS. They also applied Bootstrap to change values based on DEA obtained from small sample data and finally measured the relationship between energy efficiency and carbon emissions. The results show that BRICS has low energy efficiency as a whole but tends to increase rapidly.

Menegaki [3] used data envelopment analysis and Malmquist method in the study within the scope of European Union countries. Only national income per capita is used as output variable, while input variables are the percentage of renewable energy sources in electricity generation, energy consumption, CO_2 emission, employment rate, and capital. Kupeli and Alp [4] demonstrated the renewable energy performance of G20 countries by data envelopment analysis (DEA) and balanced performance weights method. They concluded that the results of the analysis with the balanced weights model gave more distinctive results than the classical model. Wang [5] demonstrated the performance of 109 countries using multi-criteria data envelopment analysis. In the study, CO_2 emission intensity and energy density were used as input variable, and ratio of renewable energy in electricity generation (%) was used as output variable. The study was conducted to cover the period 2005-2010. Sozen et al. [6] presented an approach for site selection of wind farms using data envelopment analysis (DEA) and TOPSIS approaches. By sorting 12 months efficiency values, they determined the most appropriate place for establish a wind farm in Turkey as examining by multi-parameter.

Lin and Long [7] applied the stochastic frontier analysis method to examine the average energy efficiency and energy saving potential of the chemical industry. The results show that energy price and operating scale are suitable for improving energy efficiency but property structure has an adverse effect. Using the stochastic frontier analysis model, Honma and Hu [8] estimated TFEE (total factor energy efficiency) scores for 47 regions across Japan between 1996 and 2008. Zhou et al. [9] extended the proposed cross-sectional stochastic frontier model. Hsiao et al. [10], using the SFA, measured TFEE for 10 countries across the Baltic Sea between 2004 and 2014.

Flippini and Hunt [11] estimated a panel "frontier" whole economy aggregate energy demand function for 29 countries over the period 1978 to 2006 using parametric stochastic frontier analysis (SFA). In this study, the energy efficiency of each country was also modeled, and it was argued that this represents a measure of the underlying efficiency for OECD countries. Lin and Du [12] presented a latent class stochastic frontier approach to measure energy efficiency under heterogeneous technologies. The proposed model has been applied to Chinese energy economy. The results show that the total energy efficiency of Chinese provinces is not high, with an average of 0.632 points from 1997 to 2010. Jin and Kim [13], to investigate energy efficiency in both economic and ecological aspects using Cobb-Douglas production function-based energy consumption, economic complexity index, and other production factors for 21 developing countries selected from Morgan Stanley Capital International in the period 1995-2016 applied a stochastic boundary analysis method. The parametric SFA method used for performance measurement is a very powerful technique.

In this study, the renewable energy efficiency levels for the BRICS countries and Turkey are assessed using the SFA method and information complexity criteria. To our knowledge, this study is the first attempt to use information complexity criteria for input-output selection task within SFA models. This paper includes two main originality since it investigates the popular assertions about "BRICST" and implements model selection procedures via the information complexity criteria in efficiency analysis.

The remainder of the study is organized as follows. In section 2, we introduce SFA methods and information criteria. Section 3 explains the application of the SFA model with renewable energy efficiency for BRICS countries and Turkey. Finally, a brief discussion is given in Section 4.

2. Materials and Methods

2.1. Stochastic frontier analysis

Stochastic frontier Analysis (SFA) is a frontier estimation method that accepts a functional form for the relationship between inputs and outputs [14]. By the SFA method, the errors occurring during production are estimated with econometric models, and the inefficiency resulting from these errors is minimized as much as possible. The SFA method is described and developed by Aigner et al. [15], Battase and Cora [16], Meusen and Vanden Browck [17]. Subsequently, Krumbhakar et al. [18], Huang and Liu [19] proposed stochastic production models that predict parameters of both stochastic frontier and inefficiency functions.

The SFA model proposed by Aigner et al. [15] is as follows:

$$\mathrm{ln} y_{it} = f(x_{j,it}, t, \beta) + v_{it} - u_{it} \tag{1}$$

where $\varepsilon_{it} = v_{it} - u_{it}$ shows the error term with $v_{it} \sim N(0, \sigma_v{}^2)$ for $u_{it} \geq 0$.

In this functional structure, the components are defined as follows:
f(.) is parametric production function (eg. Cobb- Douglas, Translog)
y_{it} : At time t, i-th output amount of decision making unit
$x_{j,it}$: At time t, i-th Vector showing entries of decision making unit
β: Unknown parameter vector

The stochastic production frontier model assumes that ε_{it} is a combined error consisting of two independent variables represented by v_{it} and u_{it}. v_{it} is independent and identically distributed error term, and $u_{it} \geq 0$ is technical inefficiency. For inefficiency, one of the semi-normal, exponential, and truncated normal and gamma distributions is used [15], Stevensen [20], Meeusen and van den Broeck [17], Greene [21]. In this study, u is inefficiency terms assumed to be an iid nonnegative truncated normal distribution.

The most common production functions used in the SFA method are Translog and Cobb-Douglas production forms [22]. In this study, Cobb - Douglas production function frontier analysis model is discussed.
Cobb-Douglas stochastic frontier model is as follows:

$$\mathrm{ln} y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j \mathrm{ln} x_{j,it} + v_{it} - u_{it} \tag{2}$$

2.2. Information criteria

The most commonly used measurements in statistical model selection are information criteria. Each criterion has different penalization terms. There are many information criteria used in the selection of statistical models. In this study, we considered three information complexity criteria ICOMP [23-26].

$$\mathrm{CICOMP} = -2logL(\widehat{M}) + d[\log(n) + 1] + 2C(\hat{\Sigma}_{\mathrm{model}}) \tag{3}$$

$$\mathrm{ICOMP}_{\mathrm{IFIM}} = -2logL(\widehat{M}) + 2C(\hat{\Sigma}_{\mathrm{model}}) \tag{4}$$

$$\mathrm{ICOMP}_{\mathrm{PEULN}} = -2\mathrm{logL}(\widehat{\mathrm{M}}) + \mathrm{d} + \log(\mathrm{n})\mathrm{C}(\hat{\Sigma}_{\mathrm{model}}) \tag{5}$$

where $L(\widehat{M})$ is likelihood function, d is the total number of parameters, n is the sample size, C is a real-valued measure of complexity [23], and $\hat{\Sigma}_{\mathrm{model}}$ represents the predicted covariance matrix of the parameter vector of the model. ICOMP information criteria penalize the covariance complexity of the model rather than directly penalizing the number of free parameters [27].

3. Application Part

In this part, we implemented the SFA to evaluate the renewable energy efficiency levels of BRICS countries and Turkey. We collected the data set from https://data.worldbank.org for the period of 2006-2015. The data set includes four inputs and one input variable. We encountered with some missing values and imputed the missing data with interpolation method for time series [28].

Firstly, we determined four potential inputs and then we eliminated them inside the SFA models. We performed the variable selection using three information complexity criteria and selected the most convenient model among all possible combinations of the input variables. The applications were conducted with R software (R Core Team, 2019). During the analysis, we benefited three R packages plm, frontier and imputeTS [28-30]. Table 1 shows the description of the input variables (x_1, x_2, x_3, x_4) and the output variable (y).

Table 1: Description of the variables

Variable	**Description**
x_1	CO_2 emission (metric ton per capita)
x_2	Primary energy (%)
x_3	Unemployment (%)
x_4	Energy intensity (level of primary energy)
y	Renewable energy (% of total final energy consumption)

Table 2 and 3 indicate the summary statistics correlation matrix for the input-output variables, respectively.

In Table 4, we reported the information criteria values for the all subsets of the input variables in SFA models. The selection results denote that all the information complexity criteria chose two inputs such as the CO_2 emissions and energy intensity for conducting the renewable energy efficiency analysis.

Table 5 shows the SFA model results for the selected inputs. In this model, the selected two inputs have significant impact on the output variable. When checking the coefficients, we can see that the CO_2 emission has the negative impact on the renewable energy efficiencies. The energy intensity provides a positive contribution on the renewable energy efficiencies.

However, time effect is not significant on the six country's efficiency levels. The Gamma parameter is also found significant and close to 1. This fact points out to the reason of the deviation of the renewable energy efficiencies which occurred because of the technical inefficiencies of the countries.

Table 2: Correlation matrix for the input and output variables

	$\boldsymbol{x_1}$	$\boldsymbol{x_2}$	$\boldsymbol{x_3}$	$\boldsymbol{x_4}$	$\boldsymbol{y}$
x_1	1	0.224708	0.319632	0.626327	-0.779227
x_2	0.224708	1	-0.771190	0.407381	-0.277025
x_3	0.319632	-0.771190	1	0.026126	-0.014327
x_4	0.626327	0.407381	0.026126	1	-0.226474
y	-0.779227	-0.277025	-0.014327	-0.226474	1

Table 3: Summary statistics for the variables

Variable	$\bar{\mathbf{X}}$	**Med**	**SD**	**Min**	**Max**
x_1	5.890	4.735	3.784	1.120	12.780
x_2	30.612	11.375	35.621	1.140	114.790
x_3	9.393	7.125	7.400	2.440	28.490
x_4	6.526	6.175	2.445	2.950	10.160
y	22.064	15.690	15.650	3.230	49.110

Table 4: Information criteria values for all the subsets of SFA models

Subset	ICOMPpeu	ICOMPpeuln	CICOMP
x_1	-93.430	-92.775	-72.958
x_2	-117.791	-107.395	-97.319
x_3	-86.938	-77.009	-66.467
x_4	-95.381	-85.057	-74.909
x_1, x_2	-123.237	-107.835	-98.671
x_1, x_3	-118.297	-103.656	-93.731
x_1, x_4	-123.797	-108.761	-99.231
x_2, x_3	-78.600	-77.972	-54.034
x_2, x_4	-77.109	-68.962	-52.543
x_3, x_4	-91.986	-76.610	-67.420
x_1, x_2, x_3	-117.202	-96.508	-88.541
x_1, x_2, x_4	-77.150	-63.624	-48.490
x_1, x_3, x_4	-117.709	-97.337	-89.049
x_2, x_3, x_4	-107.996	-87.737	-79.336
x_1, x_2, x_3, x_4	-111.545	-84.835	-78.790

Table 5: SFA results for the selected model

Coefficient	Estimate	SE	z-value	Sig.
(Intercept)	3.861395	0.084629	45.627600	<0.001
x_1	-0.086673	0.012298	-7.047500	<0.001
x_4	0.043810	0.016509	2.653700	<0.01
σ^2	1.112438	0.638565	1.742100	0.081492
Gamma	0.997640	0.001461	683.043600	<0.001
Time	0.001556	0.002687	0.579200	0.562422

Table 6 shows the yearly (2006-2015) renewable energy efficiency values, the average efficiencies (AE), and the ranks of BRICS countries and Turkey. According to results, the renewable energy efficiency values follow approximately the same pattern for each country and do not vary significantly between the years. When comparing the renewable energy efficiencies among the countries, Brazil has the best performance with approximately 97% efficiency level, and Russia has the worst one. The efficiency level of Turkey is rather weak, but it is not the worst and the average efficiency is very close to China.

Table 6: Efficiency values and the ranks for BRICS countries and Turkey

Year	BRA	RUS	IND	CHN	ZAF	TUR
2006	0.970855	0.137442	0.763710	0.339994	0.496299	0.337774
2007	0.970899	0.137866	0.764030	0.340565	0.496840	0.338345
2008	0.970944	0.138292	0.764350	0.341136	0.497381	0.338915
2009	0.970988	0.138718	0.764669	0.341707	0.497921	0.339486
2010	0.971032	0.139144	0.764988	0.342278	0.498461	0.340057
2011	0.971077	0.139572	0.765307	0.342849	0.499001	0.340627
2012	0.971121	0.140000	0.765625	0.343420	0.499541	0.341198
2013	0.971165	0.140428	0.765943	0.343991	0.500080	0.341769
2014	0.971209	0.140858	0.766261	0.344562	0.500619	0.342340
2015	0.971253	0.141288	0.766578	0.345133	0.501158	0.342911
AE	0.971054	0.139361	0.765146	0.342563	0.498730	0.340342
Rank	1	6	2	4	3	5

4. Conclusion and Discussion

Renewable energy management has been recently received great attention worldwide. Therefore, it becomes very important to use the resources efficiently for maintaining renewable energy process in terms of countries. In this paper, we measured the renewable energy efficiencies of BRICS countries compared with Turkey. We used SFA for the efficiency analysis within input selection. The information complexity criteria assisted us to decide which input set is the best on renewable energy efficiency process. The selection results pointed out to the CO_2 emission and Energy intensity as the most explanatory inputs. We observed that the selected inputs have significant effect on the renewable energy efficiencies.

According to average efficiency values, Brasilia is superior to all BRICS countries and Turkey regarding the renewable energy. Turkey's renewable energy efficiency level is very close to China and higher than Russia. Turkey is 5th country among all BRICS countries in terms of the average renewable energy efficiency scores. The renewable energy efficiency levels of BRICS and Turkey do not pretty much differ, and Turkey's performance is not the worse one. Consequently, we believe that this study will shed light on the views about the possibility of "BRICST" association.

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