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Slack-based efficiency assessment of electrical distribution regions in Ghana

***Abstract**. This paper used the Slack-based efficiency data envelopment analysis model (DEA) to assess the efficiency of electrical distribution regions (EDRs) in Ghana, using Electricity Company of Ghana as a case study, an analysis that had not been previously conducted on the ECG. Results showed that the efficiency dipped drastically in 2013, but improved from 2014 to 2016, stagnating in 2017 and dropping further in 2018. The consistency of the estimations was ensured by establishing the production frontier's form, variable returns to scale.*

***Streszczenie.** W tym artykule wykorzystano oparty na Slack model analizy danych dotyczących wydajności (DEA) do oceny wydajności regionów dystrybucji energii elektrycznej (EDR) w Ghanie, wykorzystując Electricity Company of Ghana jako studium przypadku, analizę, która nie została wcześniej przeprowadzona na EKG Wyniki pokazały, że wydajność drastycznie spadła w 2013 r., ale poprawiła się od 2014 do 2016 r., stagnacja w 2017 r. i dalszy spadek w 2018 r. Spójność szacunków została zapewniona poprzez ustalenie postaci granicy produkcji, zmiennych korzyści skali. (**Oparta na luzie ocena wydajności regionów dystrybucji energii elektrycznej w Ghanie**)*

Keywords: Slacks-based measure; Data Envelopment Analysis (DEA); Efficiency; Electricity Distribution Regions (EDRs).
Słowa kluczowe: Miara oparta na spodniach; Analiza otoczenia danych (DEA); Efektywność, regiony dystrybucji energii elektrycznej (EDR).

Introduction

Electricity is a vital public utility for the residential, commercial, industrial and service sectors. Effective management is necessary in the electrical power sector to guarantee that consumers receive high-quality electricity. Unfortunately, the unreliable electricity supply is a challenge afflicting most African countries. According to the Afro Barometer, North African countries are Africa's most reliable and regular electricity supply. Mauritius, Morocco, Egypt, Algeria, and Tunisia have power supply reliability rates of 98%, 92%, 88%, and 83%, respectively [1]. Malawi, Burundi, and Burkina Faso have the least power supply reliability rates of 12%, 11%, and 14%, respectively [1]. Often, an electricity connection does not equal a reliable electricity supply. Currently, only seven countries in Africa (excluding North African countries) can boast of electrification rates exceeding 50%, including Cameroon, Côte D'Ivoire, Gabon, Ghana, Namibia, Senegal, and South Africa [1].

There have been a wave of studies exploring sustainable power generation options with a focus on the most efficient solar systems [2]. However, the efficiency of the distribution subsector in the power system value chain is important in delivery value to the consumer. In advancing Ghana's electrification agenda, it has become necessary to analyse its efficiency and business operating performance of the electricity distribution districts due to their important role in the power supply value chain. There have been concerns about the operational performance of power distribution companies in Ghana. This concern has focused chiefly on the Electricity Company of Ghana (ECG) as it has the largest customer population and distributes power to most southern Ghana power consumers [3-5]. These discussions have highlighted ECG's operational challenges and morphed them into issues of national interest. While several efforts and investments have been made to remedy these challenges, inefficiencies persist [5].

This study, therefore, examines for the first time the efficiency of electrical distribution regions (EDR) in Ghana within the ECG's coverage since their performance affects the overall performance of the company. The study contributes to the literature on electricity distribution by incorporating system losses (technical and commercial losses) into the efficiency estimation as undesirable output using the Slacks-based Measure (SBM) in Data Envelopment Analysis (DEA). The study also extends the application of the scale elasticity hypothesis test to ascertain the form of the production frontier, which can either be constant returns to scale (CRS) or variable returns to scale (VRS) to ensure consistency in the estimation of efficiency scores.

Literature review

In [6], the definition of technical efficiency considers multiple outputs and multiple input cases where there is no possibility of increasing at least one output while holding the others at the desired levels or augmenting at least one input and vice versa. It is difficult to diminish only one input without expanding or reducing one more input or output. Also, the most extreme achievable output is given the optimum input needed to deliver a given degree of output.

The work in [7] developed the original data envelopment analysis (DEA) model, often referred to as a Charnes Cooper Rhodes (CCR) model, for channels that assume Decision-Making Units (DMU) operate with Constant returns to scale (CRS) efficiently. The modification of CCR was developed by [8] and is often referred to as the Banker, Charnes and Cooper (BCC) model.

The performance of the electricity distribution sector has attracted substantial attention since the early 1990s after the pioneering work by [9]. DEA have been applied to assess the relative efficiency of electricity distribution utilities (EDUs) [10-18]. This is the result of the wave of regulation, reform, and privatization that has been implemented in the power distribution sector in various nations [19]. Whereas these studies have been informative in other contexts, there is very little information on the performance of electricity distribution utilities in Africa and no study prior to this work for Ghana.

Studies have assessed the efficiency of EDUs or EDDs within the framework of DEA and have come up with insightful findings. The outcomes of some studies assessing efficiency have reported average inefficiency among distribution utilities [10, 11, 20]. Employing DEA to assess performance [14] found the average yearly technical (or managerial) efficiency of Australian utilities increased, while in [21] the average efficiency of Brazilian EDUs decreased.

The authors in [22] evaluated the performance of 20 electric distribution units in Sri Lanka using the DEA under constant Return to Scale (CRS) and Variable Return to Scale (VRS) frontiers. The study's selected inputs were the number of substations, low voltage line length, number of employees, operation and maintenance cost, and System Average Interruption Duration Index (calculated as total customer interruption durations per year), with sales and number of consumers considered as output variables. Their study did not capture losses as an undesirable output.

The work by [23] used panel data from 2005 to 2012 to assess India's electricity distribution utilities using a two-stage DEA with a bootstrap estimation. Their result showed that customer structure and population density positively affect the efficiency of utilities. Secondly, they find that public utilities are less efficient than private utilities in densely populated areas. Authors in [13] considered twenty-one (21) electrical distribution regions in Turkey, using a second-stage Tobit DEA model to assess efficiency and service quality in the variable business environment. Their results indicated a positive effect on efficiency when regional customer density and private ownership are considered.

[24] used DEA to benchmark 15 Caribbean power distribution countries, revealing low-efficiency levels due to lack of competition in the distribution retail industry that is difficult to overcome. Also, [25] used two-stage bootstrapped DEA technical efficiency under the VRS production frontier to assess the impact of reforms on the technical efficiency of the Peruvian utilities. They found improvements in efficiency after the reforms.

The studies reviewed employed the radial CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) DEA models. Whereas non-radial models such as the SBM are robust and have greater discriminating power [26-28], but they have not been extensively applied in the electricity distribution literature as done in this work. A summary of reviewed works is presented in Table 1.

Table 1. Summary of related works

Ref	Losses	Contribution	Limitation/Gaps	Research focus	Country of Case Study
[23]	No	Ownership and Determinants of efficiency variation using a two-stage DEA	Returns to scales hypothesis test, Slacks based measure	Efficiency evaluation of electricity distribution utilities in India	India
[29]	No	Recommendations on how to apply DEA successfully for performance improvement	Returns to scales hypothesis test, Slacks based measure	Formative evaluation of electricity distribution utilities	Portugal
[20]	Energy Loss as input	Incorporating quality of service	Returns to scales hypothesis test, Slacks based measure	Inefficiency persistence	Colombia
[13]	No	Impact of ownership on performance	Returns to scales hypothesis test, Slacks based measure	Two-stage analysis. Effect of environmental variables on efficiency	Turkey
[18]	Yes	Incorporating quality of service	Returns to scales hypothesis test, Slacks based measure	Efficiency and productivity assessment	Turkey
[11]	No	An algorithm based on DEA	Returns to scales hypothesis test, Slacks based measure	Reorganization	India
[12]	No	Sensitivity analysis	Returns to scales hypothesis test, Slacks based measure	Relative performance, sensitivity analysis and reorganization	India
[27]	No	Relationship between a KMS and variations in organizational efficiency	Returns to scales hypothesis test	Performance of electricity distribution districts based on	Taiwan
[28]	No	Integrating slacks-based measures with strong complementary slackness condition	Returns to scales hypothesis test	Ranking of EDUs	Iran
[15]	Losses as input	Impact of reforms on efficiency and productivity	Returns to scales hypothesis test, Slacks based measure	Measuring efficiency and productivity	Peru
[25]	Losses as input	Develop models to test the validity of results and the impact of reforms on performance	Returns to scales hypothesis test, Slacks based measure	Two-stage analysis. Effect of environmental variables on efficiency	Peru
This work	Losses as undesirable output	Slacks based measurement, Variable Returns to Scales hypothesis test, Incorporating losses as undesirable output in efficiency assessment of EDRs in Ghana.	Impact of environmental variables on efficiency	Efficiency assessment of EDRs in Ghana.	Ghana

These studies reviewed [8-27] did not test for the nature or form of the production frontier using the hypothesis test specified by [30]. Selecting any type of returns to scale or ignoring it can lead to misleading conclusions. Some prior EDRs studies select CRS or VRS based on assumptions such as size [25, 31, 32]. No EDRs efficiency study has empirically tested the scale elasticity property, especially using the bootstrap algorithms [34]. However, these studies employed the radial CCR and BCC DEA models. While non-radial models such as the SBM are robust and have greater discriminating power [26, 28, 33], they have not been extensively applied in electricity distribution literature. The SBM can capture non-radial slacks when estimating efficiency [34]. If these non-radial and non-zero slacks truly exist, then the CCR and BCC models overestimate the efficiency scores. The SBM has the advantage of being unit invariant, monotone (thus decreasing in each input and output slacks, dealing directly with the input excesses and the output deficits), determined only by consulting the reference set of DMUs. The SBM is not affected by statistics encompassing the whole data set and deals with negative outputs in evaluating efficiency [34, 35]. The main purpose of this paper is to assess for the first time the efficiency of electrical distribution districts of the ECG using the SBM DEA model, which in-corporates both input and output slacks in estimating efficiency scores.

This research advances the knowledge on efficiency evaluation in the electricity distribution industry in three different ways namely: (1) a premier assessment of electricity distribution regions within the Electricity Company of Ghana coverage area using DEA; (2) employing the SBM with losses (commercial and technical losses) as undesirable out-puts generated by EDRs; (3) in order to analyse the statistical characteristics of the non-parametric estimates, bootstrapping is performed. Specifically, the scale elasticity (re-turns-to-scale) hypothesis is statistically tested.

Methodology

In formalising the basic DEA CCR model, assume there are N production units or DMUs (which are EDRs in the context of this study) that are to be evaluated. The output can only be produced with the consumption of inputs and the production technology set that includes the observed EDRs, according to the axioms of ray unboundedness, strong free disability (monotonicity), and convexity. This is expressed as:

(1) $$\psi_c = \left\{ (y, x) \in \Re_+^{m+s} \mid x \text{ can produce } y \right\}$$

Where ψ_c denotes a CRS production technology. The x and y letters represent the input and output, which belong to the set of positive real numbers. In simple terms, the CCR model defines efficiency in a ratio form. The output-oriented efficiency score of a particular *EDR$_j$*, under the CRS technology, can be estimated by finding a solution to the linear programming problem presented in equation (2):

(2) $$\begin{aligned} & Max\ \varphi_0(y_0, x_0) \\ & \text{subject to:} \\ & \sum_{j=1}^{N} y_{rj}\lambda_j - \varphi y_{r0} \geq 0; \qquad \forall r = 1,2,...,s \\ & -\sum_{j=1}^{N} \lambda_j x_{ij} + x_{i0} \geq 0; \qquad \forall i = 1,2,...,m \\ & \lambda_j \geq 0; \qquad \forall j = 1,2,...,N \end{aligned}$$

In an output orientation, when the objective function $\varphi_0(y_0, x_0)=1$, the observed EDR$_0$ is radially efficient and operates on the frontier. On the other hand, $\varphi_0(y_0, x_0)<1$ if then *EDR$_0$* is radially inefficient or $\varphi_0(y_0, x_0)>1$ implies super-efficiency. Therefore, it functions beneath the frontier. These efficiency scores are specified as Farrell's technical efficiency, and they involve a radial projection of EDRs onto the boundary of the production technology [36]. The BCC or VRS technology model of [8] imposes a “convexity constraint” in equation (3) on the model that relaxes the CRS assumption, making it VRS.

(3) $$\sum_{j=1}^{N} \lambda_j = 1$$

Slacks-Based Measure (SBM)

The SBM is adopted for this study to examine how managers effectively employ resources available to generate outputs. Again, we considered N EDRs to be assessed. Each consumes inputs to generate some outputs represented by the vectors in equations (4) and (5). Equation 4 represents the input vector of all possible inputs used by a particular EDR belonging to the set of positive real numbers. Equation 5, on the other hand, represents the output vector of all output generated by a particular EDR.

(4) $$X_j = \left[x_1, x_2, ..., x_{mj} \right]^T \in \Re_+^{m \times N}$$

(5) $$Y_j = \left[y_1, y_2, ..., y_{sj} \right]^T \in \Re_+^{s \times N}$$

We assume that all data is non-zero and nonnegative, that is, $\boldsymbol{X} > \boldsymbol{0}$ and $\boldsymbol{Y} > \boldsymbol{0}$. The SBM production technology based on the VRS assumption is specified as follows:

(6) $$\Psi_v = \left\{ (y, x) \middle| \, y \leq Y\lambda, x \geq X\lambda, \sum \lambda = 1, \lambda \geq 0 \right\}$$

λ - the weight assigned to all inputs and outputs, normally referred to as the “impact factor”. $\sum \lambda = 1$ - convexity constraint for a VRS production technology.

The relative output-oriented SBM-VRS efficiency of EDR$_o$ can be obtained using the linear programming problem in equation (7):

(7) $$\begin{aligned} & \frac{1}{\hat{\rho}_o^*} = \max_{\lambda, s^-, s^+} 1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}} \\ & \text{subject to:} \\ & x_{io} = \sum_{j=1}^{N} x_{ij}\lambda_j + s_i^-; \quad \forall i = 1,\ 2, ..., m \\ & y_{ro} = \sum_{j=1}^{N} y_{rj}\lambda_j - s_r^+; \quad \forall r = 1,\ 2, ..., s \\ & \sum_{j=1}^{N} \lambda_j = 1; \qquad \forall j = 1,\ 2, ..., N \\ & \lambda_j,\ s_i^-,\ s_r^+ \geq 0, \end{aligned}$$

x_{io} - observed input, y_{ro} - observed output. λ_j - allocated coefficient or weight to the inputs and outputs determined during the optimisation process. x_{ij} and y_{rj} are the amounts of i input and r output, respectively, the observed EDR. The level of input and outputs employed by each EDR is represented by m and s, respectively. s_i^- and s_r^+ are the input and output slacks. In an output, orientation EDR$_o$ is SBM-efficient if $\rho_o^* = 1$, meaning there are no output deficits or slacks.

DEA Pre-Estimation Hypothesis Test

DEA efficiency and productivity scores are estimated regarding production technology. The production technology is specified under some assumptions. The work in [37] proposed their model under the CRS assumption, while [8] modified the CRS to propose the VRS production technology. If the production technology exhibits CRS, it implies that regions operate at an ideal scale; thus, size is irrelevant.

On the contrary, a VRS production technology implies that organisations are not operating at an ideal scale, and the size or scale of an operation is relevant. If the technology is not CRS, some EDRs may be too small or too large. Imposing CRS on the technology while it exhibits VRS may seriously distort the measure of efficiency. Likewise, statistical efficiency will be lost if one assumes VRS when the scale elasticity is constant. Testing the scale elasticity before performance assessment in the DEA is crucial to ensure consistent results. Assuming scale elasticity where the existing production technology exhibits a different one may result in some statistical errors and diverse conclusions. It is imperative to test for the underlying technology's return to scale (RTS), as varied RTS axioms can lead to diverse inferences [30]. Researchers have propounded different approaches for testing scale elasticity.

Furthermore, [38], for instance, proposed a procedure for determining the nature of the RTS of the production technology. They, however, did not provide a statistical basis to accomplish this. Also, [39] suggested the Kolmogorov-Smirnov test, a semi-parametric RTS test, to show if efficiency and productivity estimates obtained under the different scale assumptions are inconsistent [30, 40, 41]. This study employs the nonparametric bootstrapped test approach of [40] to establish economies of scale. This is based on the hypothesis that:

$$H_0 : \Psi \text{ is globally CRS} \qquad (8)$$
$$H_1 : \Psi \text{ is globally VRS}$$

The work in [34] recommended a test of RTS using some test statistics based on the bootstrapping approach. The test statistic is computed with equations (9) and (10):

$$\hat{S}_1 = N^{-1} \sum_{j=1}^{N} \left[\frac{\hat{\varphi}_j^{CRS}(y,x)}{\hat{\varphi}_j^{VRS}(y,x)} \right] \qquad (9)$$

$$\hat{S}_2 = \frac{\sum_{j=1}^{N} \hat{\varphi}_j^{CRS}(y,x)}{\sum_{j=1}^{N} \hat{\varphi}_j^{VRS}(y,x)} \qquad (10)$$

$\hat{S}_1$ - mean of ratios, $\hat{S}_2$ - ratios of means, $\hat{\varphi}_j^{CRS}(y,x)$ - CRS technical efficiency scores, $\hat{\varphi}_j^{VRS}(y,x)$ - CRS technical efficiency scores

If the null hypothesis is true, that is, if H_0 is CRS, then

$$\hat{\varphi}_j^{CRS}(y,x) = \hat{\varphi}_j^{VRS}(y,x) \qquad (11)$$

for all EDRs $(j=1,2.....,N)$ such that

.

$$\hat{\varphi}_j^{CRS}(y,x) / \hat{\varphi}_j^{VRS}(y,x) = 1 \qquad (12)$$

As a result, the null hypothesis, H_0, is rejected when Sˆ is significantly less than unity.

P-values are estimated when testing the statistical significance difference between critical values. Nevertheless, a bootstrapping technique is used to obtain suitable critical values since the distribution Sˆ under the null hypothesis, H_0 is anonymous. Few studies consider this test of scale elasticity [26, 42]. The method of [40] estimates the scale efficiency of the whole sample, referred to as global RTS. This test justifies assessing whether the scale efficiency of EDRs is significant as an added advantage to testing the sort of scale assumption.

Results and Discussions

This section presents the results of the hypothesis tests and efficiency estimations in the form of tables and figures in the following subsection.

The results of the hypothesis test to establish the scale elasticity of the dataset are shown in Table 2. The test statistics, p-values, and critical values for the test of RTS for the respective year and that for the pooled data are shown. The average yearly technical and SBM efficiency scores are represented in Table 3. The lower confidence intervals (LB_CI) and the upper confidence interval (UB_CI) generated from bootstrapping the efficiency scores. Bootstrapping help to make statistical inferences from the efficiency scores estimated. The annual average technical and SBM efficiency trend of individual EDRs is presented in Figure 2.

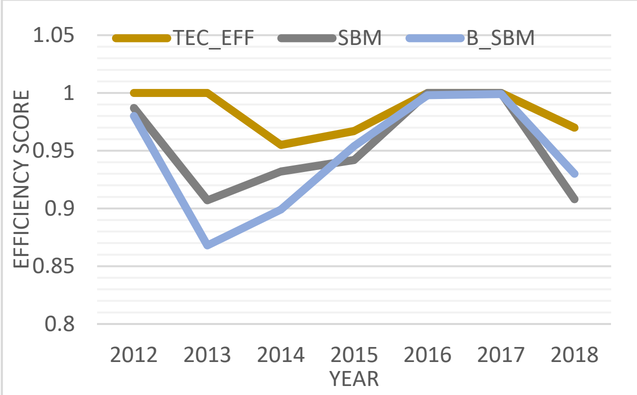

Fig. 1. Annual average SBM efficiency trend of EDRs

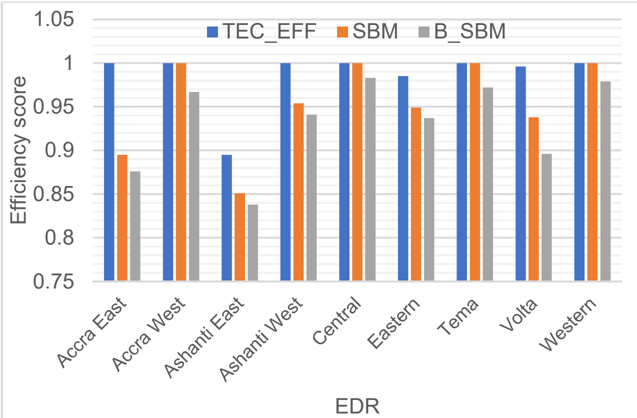

Fig. 2. Average SBM and bias-corrected SBM (B_SBM)

Table 2. Hypothesis testing of CRS vs VRS

Year	Test statistic	P-value	Critical value	RTS
2012	0.972	0.2	0.932	CRS
2013	0.977	0.03	0.98	VRS
2014	0.967	0.01	0.979	VRS
2015	0.995	0.03	0.995	VRS
2016	0.977	0.17	0.962	CRS
2017	0.959	0.1	0.952	CRS
2018	0.993	0.07	0.993	CRS
POOLED	0.932	0.01	0.9448	VRS

Table 3. Average yearly SBM efficiency scores

Year	TEC_EFF	SBM	Bias	B_SBM	LB_CI	UB_CI
2012	1.000	0.987	0.007	0.980	0.929	0.991
2013	1.000	0.907	0.039	0.868	0.722	0.910
2014	0.955	0.932	0.033	0.899	0.766	0.942
2015	0.967	0.942	-0.012	0.954	0.775	1.000
2016	1.000	1.000	0.002	0.998	1.000	1.000
2017	1.000	1.000	0.001	0.999	1.000	1.000
2018	0.970	0.908	-0.022	0.930	0.743	0.967
Average	**0.984**	**0.953**	**0.007**	**0.946**	**0.840**	**0.972**

Scale elasticity

Before assessing the performance of EDRs using the DEA approach, it is essential to establish the scale elasticity of the production technology (whether EDRs operate under CRS or VRS) to avoid extreme bias, misleading measures, or statistically inconsistent estimates of efficiency [30, 41].

Table 2 presents the test statistics, p-values, and critical values for the test of RTS. Based on [30, 41], This preliminary analysis is conducted to determine the yearly RTS and the entire data. The null hypothesis is rejected if the p-value is less than alpha (0.05), meaning the technology is not globally CRS. The outcome shows that the null hypothesis H_0 for the pooled data (that is, the technology is CRS) is rejected, implying that EDRs generally operate under the VRS

Thus, in 2012, 2016, and 2017, EDRs operated under the CRS assumption, while in 2013, 2014, and 2015 they operated under the VRS assumption. This suggests that 2012, 2016, and 2017 EDRs improved their output holistically by the same factor as their inputs increased.

Efficiency Assessment of EDRs

The yearly average technical and SBM efficiency scores of EDRs are reported together with the bias-corrected scores (B_SBM) and 95% confidence intervals (LB_CI and UB_CI) in Table 3. As discussed in the previous chapter, if an EDR's efficiency score equals 1, it is said to be 'efficient'; otherwise, it is inefficient.

The results presented in Tables 3 show that the technical efficiency scores recorded are higher than the SBM scores. This shows the robustness of the SBM model. The average overall efficiency of EDRs for the study period was 95.28%. This infers that the level of inefficiency among EDRs is 4.72% (1–0.9528= 0.0472). The highest efficiency scores were recorded in 2016 and 2017, and the lowest efficiency level was realised in 2013. Managerial efficiency for 2013 dropped by 0.0799, representing a 7.99% decline from the previous year. The decline in managerial efficiency from 2013 and marginally increasing to 2015 may be attributed in part to a drastic decline in the Gross Domestic Product of the country from 7.8% in 2012 to 5.4% in 2013 [43]. Another possible factor, is the erratic power supply (referred to as "Dumsor") experienced in the first half of 2013 which continued till 2015 [5]. The performance level improved marginally in 2014 and 2015.

The minimal dip in GDP growth is credited to the negative growth in the manufacturing subsector and industry sector, resulting from the disturbingly insufficient power supplied [44]. Even though the Ghanaian economy experienced a gradual dip in real GPD growth from 2014 to 2016 [44], an increase in efficiency from 2014 to 2017 can be attributed to the roll-out of projects by the utility provider to improve revenue mobilisation and reduce technical and commercial losses [50] and the growth of the industry sector of the Ghanaian economy [3]. These factors may have contributed to a rise in the level of efficiency. However, decline in managerial efficiency in 2018 may be attributed to the rise in losses from 3.8% to 4.4% of electricity distributed [45].

Figure 1 shows the efficiency trend from 2012 to 2018, and the difference in estimated scores of the technical efficiency (TEC_EFF), the SBM and the bootstrapped SBM scores (B_SBM). It clearly shows the discriminatory power of the SBM model and the biases in the efficiency score which has been removed via bootstrapping.

Figure 2 shows the average technical efficiency, SBM and the bootstrapped SBM scores for the various EDRs over the study period. Six EDRs namely, Accra East, Accra West, Ashanti West, Central Tema and Western were efficient. The least efficiency score of 0.895 was recorded by Ashanti East. The SBM efficiency scores reduced the number of fully efficient EDRs to four. After purging the SBM score of biases no EDR was fully efficient. However, in general, the performance of individual EDRs is above average.

Conclusions

The SBM was used to test the consistency of power distribution regions. A detailed methodological overview of the scale elasticity test of efficiency and productivity performance using ideal scales with or without relevant technology was presented using mathematical modelling. Thereafter, these methodologies were leveraged to determine EDRs operating CRS or VRS to avoid statistical CRS. The outcome shows that the null hypothesis H_0 for the pooled data (that is, the technology is CRS) is rejected, implying that EDRs generally operate under the VRS frontier. assumption. This means altering input levels may not reduce or in-crease output levels proportionately. However, the null hypothesis was not rejected for the annual results in 2012, 2016, and 2017. assumption. This means altering input levels may not reduce or in-crease output levels proportionately. However, the null hypothesis was not rejected for the annual results in 2012, 2016, and 2017.inconsistency and extreme biasing. The production frontier exhibited a CRS form in 2012, 2016, 2017 and 2018. From 2013 to 2015, the production frontier exhibited a VRS form, which influenced the nature of the global production frontier to be VRS in form. The efficiency of EDRs, though not so discouraging, needs a greater amount of improvement to turn around the operational performance of the utility company. The low-efficiency levels obtained in this work indicate a lack of competition in the retail distribution industry, which the utility provider should strive to introduce.

Future studies

In future research it would be interesting to see how bootstrapping performs against Monte Carlo methods which can utilize computational algorithms to predict future efficiencies depending on the weighting on the various inputs and outputs. This will help the electricity distribution companies with policies and focus on effort or capital expenditure on their infrastructures or uplift of their resources. Future work on electricity distribution in Ghana can look at the effect of losses on the efficiency of EDRs. Also, the impact of environmental variables on efficiency can be investigated since EDRs operates with a business ecosystem that is subject to some economic shocks.

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