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Efficiency benchmarking of Nigerian electricity distribution companies using an integrated DEA–Shannon entropy

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Abstract

This study evaluates the relative operational efficiency of the eleven legacy Nigerian electricity distribution companies (DisCos) over 2018–2025 using an integrated Data Envelopment Analysis (DEA)–Shannon entropy framework. The DEA production specification treats customers under estimated billing as the input-side operating burden, with metered customers, revenue collected, and energy billed in gigawatt-hours (GWh) as desirable outputs. Three DEA specifications are estimated annually: constant returns to scale (CRS), input-oriented variable returns to scale (IVRS), and output-oriented variable returns to scale (OVRS). Their efficiency scores are combined using year-specific Shannon entropy weights to obtain a composite Shannon Efficiency Score (SES) for each DisCo. Results reveal substantial heterogeneity in technical, scale, and output-oriented efficiency across DisCos and over time, with IKEDC and EKEDC generally among the stronger performers. Shannon entropy does not modify the underlying DEA frontiers or individual efficiency scores; it derives information-based weights from the annual score distributions and combines them at the aggregation and ranking stage. Because metered customers and customers under estimated billing enter the DEA production specification directly, the resulting scores inherently reflect metering status and should not be interpreted as an independent statistical test of the relationship between metering performance and operational efficiency. The integrated DEA–Shannon entropy framework provides a reproducible approach for combining complementary DEA efficiency perspectives and benchmarking the relative performance of Nigerian electricity distribution companies.

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1. Introduction

Electricity distribution companies (EDCs) in Nigeria play a prominent role in ensuring consistent electricity supply and reliable customer service. EDCs emerged after the privatization of the Nigerian power sector in 2013, which brought several changes in structure, operations, and management. These companies became integral parts of the Nigerian Electricity Supply Industry (NESI), which encompasses power generation, transmission, and distribution. EDCs are responsible for delivering electricity to stakeholders, including households, industries, and commercial entities [1].

Before privatization, the government managed the power

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sector in Nigeria, which was associated with issues such as inefficiencies, significant losses, and inadequate infrastructure. The primary purpose of privatizing the power sector and establishing EDCs was to attract investment and technical expertise and to improve efficiency, service delivery, and management. It was also expected that EDCs would improve infrastructure and customer service and reduce technical losses. Improvements have also been observed in metering systems, which provide more accurate measurement of power consumption and can reduce reliance on estimated billing.

Despite privatization, Nigerian EDCs continue to face several challenges, including power-supply deficits, high aggregate technical, commercial, and collection (ATC&C) losses, inadequate metering, regulatory limitations, and financial constraints. Addressing these challenges requires improvements in operational efficiency and stronger stakeholder collaboration, which can support a sufficient and sustainable electricity supply for Nigerians.

As of December 2024, the Nigerian Electricity Regulatory Commission (NERC) identifies twelve electricity distribution licensees in the Nigerian Electricity Supply Industry (NESI), comprising Aba Power Limited Electric (APLE) and the eleven legacy/successor Distribution Companies (DisCos) associated with the 2013 electricity-sector privatization [2]. The eleven legacy DisCos are Abuja Electricity Distribution Company, Benin Electricity Distribution Company, Eko Electricity Distribution Company, Enugu Electricity Distribution Company, Ibadan Electricity Distribution Company, Ikeja Electric, Jos Electricity Distribution Company, Kaduna Electricity Distribution Company, Kano Electricity Distribution Company, Port Harcourt Electricity Distribution Company, and Yola Electricity Distribution Company.

The present study is restricted to these eleven legacy/successor DisCos because they provide a consistent longitudinal set of decision-making units over the 2018–2025 study period. Aba Power was excluded because it is not one of the eleven successor DisCos and a complete, consistently defined 2018–2025 series for all DEA input and output variables was not available on the same basis as for the legacy DisCos. This restriction preserves comparability of the annual DEA frontiers and avoids introducing an unbalanced DMU panel. These companies are privately owned but are regulated by the Nigerian Electricity Regulatory Commission to ensure compliance with industry standards, service quality requirements, customer protection guidelines, and operational accountability.

Despite privatization of the electricity sector, Nigerian electricity distribution companies continue to face several operational challenges, including inadequate metering, high aggregate technical, commercial, and collection losses, power-supply deficits, tariff-related concerns, financial constraints, and uneven service delivery in urban and rural areas [3], [4].

Despite ongoing metering initiatives, a substantial metering gap remains within the Nigerian electricity distribution sector. According to the Nigerian Electricity Regulatory Commission, as of 31 December 2025, 6,966,584 out of 12,163,412 active registered electricity customers across the eleven successor DisCos were metered, representing a metering rate of 57.27%. Consequently, approximately 42.73% of active registered customers remained unmetered at the end of the study period. The Federal Government, NERC, and the DisCos have continued to implement metering initiatives aimed at reducing the number of customers subject to estimated billing [5].

The Nigerian government introduced the Multi-Year Tariff Order (MYTO) framework to guide reforms in electricity tariffs and better reflect the cost of supply. MYTO is intended to align electricity tariffs more closely with production costs and provides a framework for regular tariff reviews. The framework also seeks to promote a fair system despite challenges posed by the socio-political climate, with customers receiving better power supply contributing more toward its cost. Reducing load shedding and power outages will also depend on addressing the Transmission Company of Nigeria's (TCN) challenges in delivering electricity effectively to EDCs. Efforts are also required to narrow the electricity-supply gap between urban and rural areas [6].

To address these issues, this study evaluates the relative efficiency of the eleven legacy Nigerian Electricity Distribution Companies over the period 2018–2025 using an integrated Data Envelopment Analysis (DEA)–Shannon entropy framework. The DEA specification treats the number of customers under estimated billing as the input-side operating burden, while metered customers, revenue collected, and energy billed in gigawatt-hours (GWh) are considered desirable outputs. Efficiency is evaluated annually under constant returns to scale (CRS), input-oriented variable returns to scale (IVRS), and output-oriented variable returns to scale (OVRS). The resulting DEA efficiency scores are subsequently combined using Shannon entropy weights to obtain a composite Shannon Efficiency Score (SES), thereby providing an integrated ranking based on the complementary information contained in the three DEA specifications.

The main contributions of this study are fourfold. First, it provides a longitudinal assessment of the relative efficiency of Nigerian electricity distribution companies over the period 2018–2025. Second, it explicitly incorporates customer metering status by distinguishing between customers remaining under estimated billing and metered customers, thereby capturing an important operational dimension of electricity distribution performance. Third, it integrates the efficiency results obtained from CRS, IVRS, and OVRS using Shannon entropy to reduce ranking ambiguity and produce a composite efficiency measure. Finally, the study provides empirical insights for policymakers, regulators, and electricity distribution companies concerning variations in technical and scale efficiency, metering performance, revenue collection, and energy billed across the Nigerian power distribution sector.

2. Data envelopment analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric technique for evaluating the relative efficiency of comparable decision-making units (DMUs) that use multiple inputs to produce multiple outputs [7]. Originally introduced by Charnes, Cooper, and Rhodes, DEA constructs an empirical best-practice frontier against which the relative performance of each DMU is assessed [7].

The original DEA formulation developed by Charnes, Cooper, and Rhodes, commonly referred to as the CCR model, assumes constant returns to scale (CRS) [7]. Banker, Charnes, and Cooper subsequently extended the DEA framework by introducing the BCC model, which allows for variable returns to scale (VRS) and enables pure technical efficiency to be distinguished from scale efficiency [8]. Both CRS and VRS DEA models may be formulated using either input-oriented or output-oriented approaches [9].

In an input-oriented DEA model, efficiency is assessed by determining the maximum proportional reduction in inputs that can be achieved while maintaining the observed level of outputs. In contrast, an output-oriented model evaluates the maximum proportional expansion of outputs that can be achieved while maintaining the observed input levels. The choice of orientation generally depends on the production context and on whether decision-makers have greater control over inputs or outputs.

DEA is non-parametric and therefore does not require an a priori specification of the functional relationship between inputs and outputs. Instead, the efficiency frontier is constructed directly from observed data, allowing DMUs with multiple inputs and outputs to be compared relative to the best-performing units in the sample. This characteristic makes DEA particularly suitable for benchmarking electricity distribution companies, where operational performance is represented by several simultaneous input and output indicators.

3. Literature review: DEA applications in electricity distribution

The literature includes traditional DEA methods such as CCR and BCC, as well as integrated approaches combining DEA with techniques such as fuzzy logic, machine learning, and artificial intelligence to evaluate the performance of EDCs in various countries. This study reviews DEA-based assessments of EDC performance within and outside Nigeria.

Olanrele [10] assessed the technical efficiency of the 11 Nigerian electricity distribution companies using data envelopment analysis, with data covering the period 2015–2022. The study used network losses and aggregate technical, commercial, and collection losses as inputs, while electricity supply, proxied by energy received by each DisCo, was treated as the output. The findings indicated that the eleven DisCos exhibited varying degrees of technical inefficiency and that the efficiency performance of several companies deteriorated during the COVID-19 period.

Cayir Ervural [11] presented a new hybrid methodology in 2020 to evaluate the efficacy of 21 Turkish EDCs. The new hybrid method was developed using an integration of DEA with Artificial Neural Networks (ANNs). The method enhances the decision-making process and tackles issues in evaluating EDCs' operational performance. The study found that EDCs in Turkey's eastern region were less efficient.

Núñez *et al.* [12] used an advanced meta-cluster frontier analysis method to assess the 236 Spanish EDCs. The study found that the less efficient companies, which are smaller in size, received higher remuneration. Furthermore, the study estimated that significant yearly savings of about 174 million euros can be achieved by improving the efficiency of these EDCs.

Mirza *et al.* [13] investigated the technical efficiency and total factor productivity of Pakistani electricity distribution companies over the period 2006–2016. The study employed stochastic frontier analysis to estimate technical efficiency and used the Malmquist Productivity Index to decompose changes in total factor productivity. Their findings highlighted changes in technical efficiency, scale performance, productivity, and service-quality conditions across the distribution companies.

Vesterberg *et al.* [14] examined the technical efficiency of Swedish electricity distribution firms and investigated the relationship between small- and micro-scale electricity generation and distribution-grid efficiency. The study employed a two-stage Data Envelopment Analysis framework together with a double-bootstrap procedure. The results revealed considerable heterogeneity in the efficiency of the distribution companies and did not indicate that a greater share of small-scale generation was systematically associated with lower operational efficiency.

Patyal *et al.* [15] used an innovative methodology to examine Indian EDCs from 2015 to 2019. The methodology involved integrated resource planning (IRP) combined with DEA and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The study revealed a significant relationship between the efficiency of EDCs and resource allocation and environmentally sustainable practices. EDCs with superior performance in these segments were ranked higher on the DEA-IRP-TOPSIS scale. In addition to being a benchmarking tool, this thorough method gives utility managers the information they need to enhance efficiency and effectively handle regulatory requirements.

Omrani *et al.* [16] used advanced methodologies to analyse 39 Iranian EDCs from 2011 to 2020. In contrast to DEA and corrected ordinary least squares (COLS), the support vector regression (SVR) model showed an exceptional average efficiency score of 0.774, demonstrating SVR's prudent approach. According to the fuzzy-TOPSIS method, more than half of the EDCs had exceptional performance.

Sánchez-Ortiz *et al.* [17] applied DEA window analysis to evaluate the efficiency of five Spanish EDCs between 2006 and 2015. The study found that the Spanish electricity sector faced challenges mainly due to overcapacity and tariff deficits. Moreover, the study suggested possible ways to enhance efficiency by implementing better laws and removing outside restrictions.

Fallahi *et al.* [18] evaluated the performance of 39 Iranian EDCs using a robust DEA model that incorporates uncertainty and external factors. The study found that a slight increase in productivity may tend to low-efficiency changes rather than technological advancements. Additionally, the study reported that large and small companies had consistent efficiencies and operated in urban and provincial areas. This offers encouraging opportunities for expansion and improvement across various company sizes and regions.

3.1. Research gap

A review of Scopus-indexed literature published between 2014 and 2025 using the keywords "DEA" and "energy efficiency" indicates that relatively limited attention has been given to the efficiency assessment of Nigerian electricity distribution companies using Data Envelopment Analysis. In contrast, studies from other countries have increasingly applied both conventional and advanced DEA approaches, sometimes in combination with methods such as TOPSIS, machine learning, and artificial intelligence, to evaluate electricity distribution performance. The reviewed studies employ a wide range of input and output variables, with customer-related indicators appearing frequently in the evaluation of electricity distribution performance. However, most studies treat customers as an aggregate measure and do not distinguish between metered and unmetered or estimated-billing customers. This distinction is particularly relevant in the Nigerian electricity distribution sector, where the proportions of metered and estimated customers vary considerably across DisCos.

To address this gap, the present study evaluates the relative performance of the eleven legacy Nigerian electricity distribution companies over the period 2018–2025 using an integrated DEA–Shannon entropy framework. The revised production specification treats the number of customers remaining under estimated billing as the input-side operating burden, while metered customers, revenue collected, and energy billed are treated as desirable outputs. Efficiency is assessed annually under CRS, IVRS, and OVRS specifications, and the resulting DEA efficiency scores are subsequently integrated using Shannon entropy weights to obtain a composite Shannon Efficiency Score. This approach allows the study to incorporate the operational significance of customer metering status while providing a single composite ranking that can differentiate among DisCos when the individual DEA specifications yield similar or competing rankings.

3.2. Performance indicators and data source

The DEA dataset used in this study was constructed from official electricity-sector data published by the National Bureau of Statistics (NBS) under the series *Nigeria Electricity Report: Energy Billed, Revenue Generated and Customers by DISCOs*, Reference ID: NGA-NBS-ELECT [19]. The dataset covers the eleven legacy/successor Nigerian electricity distribution companies over the period 2018–2025.

The four variables used in the DEA specification are the number of customers under estimated billing, the number of metered customers, revenue collected, and energy billed. Energy billed, measured in gigawatt-hours (GWh) [20, 21], is used as the electricity-output measure in the DEA model. Because the underlying source data are reported at monthly and quarterly frequencies, the observations were harmonized to obtain one annual DEA dataset for each DisCo. Year-end customer counts were represented by the last available observation in each calendar year, while annual revenue and energy billed were obtained by aggregating the available monthly observations within each year.

The NERC Third Quarter 2025 Report was additionally consulted as an independent source for cross-checking the regulatory and operational context of the Nigerian Electricity Supply Industry during 2025, including DisCo-level commercial and operational performance indicators [22].

For full reproducibility, the complete harmonized annual input–output dataset used to estimate the DEA models is provided in Supplementary Table S1. Supplementary Table S2 documents the corresponding source mapping, annualization procedure, working source file, and official NBS resource used for each variable and year. The values reported in Supplementary Table S1 are the observations used directly to generate the CRS, IVRS, and OVRS efficiency scores reported in Tables 3–5.

The study population consists of the eleven legacy/successor Nigerian electricity distribution companies used as decision-making units (DMUs): AEDC, BEDC, EKEDC, EEDC, IBEDC, IKEDC, JEDC, KDEDC, KEDC, PHEDC, and YEDC, as shown in Table 1. Although NERC currently recognizes Aba Power Limited Electric (APLE) as an additional distribution licensee, APLE was excluded from the longitudinal DEA sample because it was not one of the eleven successor DisCos established through the 2013 electricity-sector privatization and comparable observations for all selected DEA variables were not available for APLE throughout the complete 2018–2025 study period. Maintaining the same eleven DMUs in each annual DEA model preserves temporal comparability of the efficiency frontiers and avoids changes in the reference technology arising solely from changes in sample composition.

The DEA variables were selected to represent the production and operational characteristics relevant to electricity distribution and to remain consistent with the objective of evaluating relative operational efficiency. The specific treatment of the selected input and desirable output variables is described in the following subsections, while tariff is excluded from the empirical DEA specification because it is substantially regulator-determined.

3.2.1. Input variable

The DEA specification distinguishes between variables that represent undesirable operating burdens, desirable performance outcomes, and externally regulated factors. The number of estimated customers is treated as an input-side undesirable service burden. A high number of customers under estimated billing reflects incomplete metering coverage and represents an operational condition that a distribution company seeks to reduce while improving service delivery. In the output-oriented DEA model, this variable is held at its observed level while the potential proportional expansion of desirable outputs is evaluated.

Tariff was excluded from the DEA production model because electricity tariffs in Nigeria are substantially determined within the regulatory framework administered by the Nigerian Electricity Regulatory Commission (NERC), particularly through the Multi-Year Tariff Order and related tariff-review mechanisms. Individual DisCos therefore do not exercise unrestricted managerial control over tariff levels. Accordingly, tariff is not treated as either a DEA input or output and does not enter the Shannon entropy aggregation or any second-stage empirical analysis in this study.

3.2.2. Output variables

The number of customers supplied through functional metering systems is treated as a desirable output because the expansion of metering coverage represents an improvement in service delivery, billing transparency, consumption measurement, and a reduction in dependence on estimated billing.

Revenue collected (million naira) is treated as a desirable financial output and represents the amount of revenue realized by each DisCo from its electricity distribution and billing activities during the year.

Energy billed is treated as the electricity-output variable in the DEA model. It represents the quantity of electrical energy billed by each DisCo to its customers and is measured in gigawatt-hours (GWh). The underlying monthly observations were obtained from the NBS electricity data series and aggregated over each calendar year to obtain the annual value used in the DEA analysis. Thus, for DisCo j in year t, annual energy billed is computed as:

$$EB_{jt} = \sum_{m=1}^{12} EB_{jtm}, \tag{1}$$

where EB_{jtm} denotes the energy billed by DisCo j in month m of year t. Eq. (1) therefore represents the aggregation of the monthly energy-billed observations into the annual GWh output used in the DEA analysis. Where the source dataset contained the available monthly observations for a given year, those observations were summed consistently to construct the corresponding annual value. The resulting annual values for 2018–2025 are reported in Supplementary Table S1, while their source and harmonization procedure are documented in Supplementary Table S2.

4. Adopted methodology

Data Envelopment Analysis (DEA) provides a nonparametric framework for evaluating the relative efficiency of decision-making units (DMUs) that use multiple inputs to produce multiple outputs. In electricity distribution studies, DEA is useful for comparing the relative performance of distribution companies operating under comparable production conditions. However, the efficiency scores and rankings obtained from DEA may vary depending on the returns-to-scale assumption and model orientation adopted. In addition, more than one DMU may be identified as efficient under a particular DEA specification, which can limit discrimination among the evaluated units.

To obtain a more integrated assessment of relative performance, this study employs three complementary DEA specifications: constant returns to scale (CRS), input-oriented variable returns to scale (IVRS), and output-oriented variable returns to scale (OVRS). The three models are estimated independently for each year using the same set of eleven Nigerian electricity distribution companies and the same DEA production specification. The resulting efficiency scores therefore represent alternative but related efficiency perspectives based on different returns-to-scale assumptions and model orientations.

The annual CRS, IVRS, and OVRS efficiency results are subsequently integrated using Shannon entropy. In the present study, Shannon entropy is applied to the distributions of the three DEA efficiency-score columns rather than directly to the original input and output variables. The purpose of the entropy procedure is to quantify the relative discriminatory information contained in each DEA specification. A DEA model whose annual efficiency scores exhibit greater dispersion contains more discriminatory information and therefore receives a larger entropy weight, whereas a model whose scores are more uniform across the DMUs receives a smaller weight.

The resulting year-specific entropy weights are used to aggregate the CRS, IVRS, and OVRS efficiency scores into a single composite Shannon Efficiency Score (SES) for each DisCo. This procedure provides a systematic way of combining the complementary information contained in the three DEA models and provides additional differentiation at the composite aggregation and ranking stage. It is important to emphasize that Shannon entropy is not used in this study as an outlier-detection, noise-correction, data-cleaning, or robust-estimation procedure. The entropy stage does not modify the original observations or correct for measurement error. Its role is limited to deriving objective weights from the annual dispersion of the DEA efficiency-score distributions and using those weights in the construction of the composite SES.

The methodological framework therefore consists of two sequential stages. First, the CRS, IVRS, and OVRS DEA models are estimated separately for each year. Second, the resulting annual DEA efficiency scores are organized into an efficiency matrix and combined using the Shannon entropy weighting procedure. The complete mathematical formulation of this integrated DEA–Shannon entropy framework is presented in the following subsection.

Previous studies have applied Shannon entropy in conjunction with DEA for several distinct methodological purposes and sectors. Lee [23] used Shannon entropy to combine DEA cross-efficiency scores for ranking DMUs, illustrated through an application to commercial banks. Yesilaydin *et al.* [24] used Shannon entropy to determine input-variable weights within a DEA-based assessment of healthcare access and quality efficiency across countries. Yang *et al.* [25] employed a Shannon-DEA procedure for eco-efficiency evaluation of paper mills, while Lo Storto [26] combined DEA cross-efficiency and Shannon entropy for ecological-efficiency ranking of cities. Peykani *et al.* [27] proposed a Shannon-entropy approach for DEA input/output-variable selection, whereas Fathi and Saen [28] integrated network DEA and Shannon entropy for sustainability evaluation of transportation supply chains. Figure 1 illustrates the integrated DEA approach with Shannon's entropy.

Table 1: Eleven legacy/successor Nigerian electricity distribution companies included as DMUs in the study.

S/No.	EDC	DMU	Region	No. of states covered	States covered
1	Abuja	AEDC	North Central	4	Kogi, Niger, Nasarawa, and the Federal Capital Territory (Abuja)
2	Benin	BEDC	South-South	4	Edo, Delta, Ondo, and Ekiti
3	Eko	EKEDC	South-West	1	Lagos State (partially)
4	Enugu	EEDC	South-East	5	Abia, Anambra, Ebonyi, Enugu, and Imo
5	Ibadan	IBEDC	South-West	5	Oyo, Ogun, Osun, Kwara, and Ekiti State (partially)
6	Ikeja	IKEDC	South-West	1	Lagos State (partially)
7	Jos	JEDC	North Central	4	Plateau, Bauchi, Benue, and Gombe
8	Kaduna	KDEDC	North-West	4	Kaduna, Sokoto, Kebbi, and Zamfara
9	Kano	KEDC	North-West	4	Kano, Katsina, Jigawa, and parts of Bauchi
10	Port Harcourt	PHEDC	South-South	4	Rivers, Cross River, Bayelsa, and Akwa Ibom
11	Yola	YEDC	North-East	4	Adamawa, Borno, Taraba, and Yobe

4.1. Mathematical formulation of the integrated DEA–Shannon entropy model

To make the adopted methodology reproducible, this study provides the mathematical formulation of the integrated Data Envelopment Analysis and Shannon entropy procedure [29]. Let there be n decision-making units, denoted by DMU_j, where $j = 1, 2, \ldots, n$. In this study, the decision-making units are the eleven Nigerian Electricity Distribution Companies. Each DMU_j uses m input variables to produce s output variables.

Let x_{ij} denote the value of input i used by DMU_j, where $i = 1, 2, \ldots, m$, and let y_{rj} denote the value of output r produced by DMU_j, where $r = 1, 2, \ldots, s$.

In the DEA specification, the number of estimated customers is treated as the input-side undesirable operating burden, while the number of metered customers, revenue collected, and energy billed are treated as desirable outputs. Tariff is excluded from the DEA production specification because it is substantially regulator-determined and is not treated as either an input or an output in the empirical analysis.

The DEA analysis was carried out separately for each year within the study period. Therefore, for each year, the eleven EDCs were treated as separate DMUs and evaluated using CRS, IVRS, and OVRS models [30].

4.1.1. CRS DEA model

The constant returns to scale (CRS) model assumes that proportional changes in inputs are associated with proportional changes in outputs. For a given DMU_o, the input-oriented CRS model is formulated as: $\min_{\theta,\lambda} \theta$, subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i = 1, 2, \ldots, m, \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \qquad r = 1, 2, \ldots, s, \tag{3}$$

$$\lambda_j \geq 0, \qquad j = 1, 2, \ldots, n. \tag{4}$$

Here, θ represents the technical efficiency score of DMU_o under the CRS assumption, while λ_j is the intensity variable assigned to peer DMU j. A value of $\theta = 1$ indicates efficiency, whereas $\theta < 1$ indicates inefficiency.

4.1.2. IVRS DEA model

The input-oriented variable returns to scale model extends the CRS model by adding a convexity constraint. For DMU_o, the IVRS model is formulated as $\min_{\theta,\lambda} \theta$, subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i = 1, 2, \ldots, m, \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \qquad r = 1, 2, \ldots, s, \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{7}$$

$$\lambda_j \geq 0, \qquad j = 1, 2, \ldots, n. \tag{8}$$

The convexity condition in Eq. (7) imposes variable returns to scale. The resulting score measures pure technical efficiency after scale effects have been taken into account.

4.1.3. OVRS DEA model

The output-oriented variable returns to scale model evaluates how much a DMU can proportionally expand its outputs while using the same input levels. For DMU_o, the OVRS model is formulated as $\max_{\phi,\lambda} \phi$, subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \qquad i = 1, 2, \ldots, m, \tag{9}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi y_{ro}, \qquad r = 1, 2, \ldots, s, \tag{10}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{11}$$

$$\lambda_j \geq 0, \qquad j = 1, 2, \ldots, n. \tag{12}$$

Here, ϕ represents the proportional output-expansion factor. The output-oriented technical efficiency score is

$$TE_{\text{OVRS}} = \frac{1}{\phi}. \tag{13}$$

A value of $TE_{\text{OVRS}} = 1$ indicates efficiency, whereas a value below one indicates output inefficiency.

4.1.4. Shannon entropy weighting of DEA efficiency results

In this study, Shannon entropy [31] is applied to the efficiency scores generated by the alternative DEA specifications rather than directly to the original input and output variables. Its purpose is to quantify the relative informational contribution of the efficiency-score distributions produced by the CRS, IVRS, and OVRS models and to derive objective weights for their subsequent aggregation.

For each year t, let $E_{jl}^{(t)}$ denote the efficiency score of DMU_j obtained from DEA model l, where

$$j = 1, 2, \ldots, n, \qquad n = 11, \tag{14}$$

and

$$l = 1, 2, 3, \tag{15}$$

with

$$M_1 = \text{CRS}, \qquad M_2 = \text{IVRS}, \qquad M_3 = \text{OVRS}. \tag{16}$$

The Shannon entropy procedure is applied independently to the three annual DEA efficiency-score columns. For each model, the corresponding efficiency scores across the eleven DMUs are normalized before the entropy, degree of diversification, and model weight are calculated.

Within this framework, a DEA model whose annual efficiency scores exhibit greater dispersion contains relatively more discriminatory information and therefore receives a larger entropy-derived weight. Conversely, a model whose efficiency scores are more uniform across the DMUs contains less discriminatory information and receives a smaller weight.

The resulting Shannon weights represent the relative informational contribution of the CRS, IVRS, and OVRS efficiency results to the construction of the composite Shannon Efficiency Score (SES). Shannon entropy does not modify the underlying DEA frontiers or the individual efficiency scores. Rather, its role is limited to deriving weights from the annual distributions of the DEA efficiency results and using those weights at the composite aggregation stage. The complete normalization, entropy, diversification, weighting, and SES aggregation procedure is presented in Subsections 4.1.5 and 4.1.6.

4.1.5. Construction of the DEA efficiency matrix

To integrate the DEA results with Shannon entropy in a transparent and reproducible manner, the annual efficiency scores obtained from the alternative DEA specifications are first organized into a common efficiency matrix. The entropy procedure is therefore applied to the DEA efficiency results rather than directly to the original input–output data. This approach follows the principle of combining efficiency results obtained from different DEA models using Shannon entropy [32].

For each year t, three DEA specifications are estimated independently using the same set of eleven decision-making units (DMUs): the constant returns to scale model (CRS), the input-oriented variable returns to scale model (IVRS), and the output-oriented variable returns to scale model (OVRS).

The same DEA production specification is maintained across the three models. The number of customers under estimated billing is treated as the input-side operating burden, whereas the number of metered customers, revenue collected, and energy billed are treated as desirable outputs.

Tariff is excluded from the DEA production frontier because electricity tariffs in Nigeria are substantially determined within the regulatory framework administered by the Nigerian Electricity Regulatory Commission (NERC). Accordingly, tariff is not treated as either an input or an output in the empirical DEA specification.

Using the notation introduced in the preceding subsection, the three DEA models are defined as:

$$M_1 = \text{CRS}, \qquad M_2 = \text{IVRS}, \qquad M_3 = \text{OVRS}. \tag{17}$$

Thus, for each year, exactly three DEA efficiency-result vectors are generated. These correspond to the CRS, IVRS, and OVRS specifications and constitute the three efficiency perspectives to be integrated using Shannon entropy.

The annual DEA efficiency matrix is therefore written as:

$$\mathbf{E}^{(t)} = \begin{bmatrix} E_{11}^{(t)} & E_{12}^{(t)} & E_{13}^{(t)} \\ E_{21}^{(t)} & E_{22}^{(t)} & E_{23}^{(t)} \\ \vdots & \vdots & \vdots \\ E_{n1}^{(t)} & E_{n2}^{(t)} & E_{n3}^{(t)} \end{bmatrix}, \qquad n = 11, \tag{18}$$

where the first, second, and third columns contain the CRS, IVRS, and OVRS efficiency scores, respectively. Accordingly,

$$E_{j1}^{(t)} = E_{j,\text{CRS}}^{(t)}, \tag{19}$$

$$E_{j2}^{(t)} = E_{j,\text{IVRS}}^{(t)}, \tag{20}$$

and

$$E_{j3}^{(t)} = E_{j,\text{OVRS}}^{(t)}. \tag{21}$$

The three DEA specifications entering the integration are summarized in Table 2.

For each year from 2018 to 2025, the construction of $\mathbf{E}^{(t)}$ proceeds as follows:

1. Construct the annual dataset for the eleven legacy/successor Nigerian electricity distribution companies.

Table 2: DEA models used in the DEA–Shannon entropy integration.

Model	Notation	Returns to Scale	Orientation
1	CRS	Constant	Input-oriented
2	IVRS	Variable	Input-oriented
3	OVRS	Variable	Output-oriented

2. Apply the same DEA production specification to all DMUs, with customers under estimated billing treated as the input and metered customers, revenue collected, and energy billed treated as desirable outputs.
3. Estimate the CRS model for all eleven DMUs and record the resulting efficiency scores as the first column of $\mathbf{E}^{(t)}$.
4. Estimate the IVRS model for all eleven DMUs and record the resulting efficiency scores as the second column of $\mathbf{E}^{(t)}$.
5. Estimate the OVRS model for all eleven DMUs and record the resulting efficiency scores as the third column of $\mathbf{E}^{(t)}$.
6. Use the resulting 11×3 DEA efficiency matrix as the input to the Shannon entropy aggregation procedure.

Accordingly, the Shannon entropy stage operates on the 11×3 matrix of DEA efficiency scores rather than on the original input–output data matrix. Each column of $\mathbf{E}^{(t)}$ represents one explicitly defined DEA efficiency perspective, and no additional unspecified or randomly generated pseudo-models are included in the principal analysis.

The resulting matrix $\mathbf{E}^{(t)}$ therefore provides the complete input to the Shannon entropy aggregation stage. The relative informational contribution of its CRS, IVRS, and OVRS columns is determined through the normalization, entropy, diversification, and weighting procedure described in the following subsection.

4.1.6. Shannon entropy aggregation and efficiency score

Following the construction of the annual DEA efficiency matrix $\mathbf{E}^{(t)}$, Shannon entropy is applied directly to the efficiency results generated by the three DEA specifications, namely CRS, IVRS, and OVRS. This formulation follows the principle of combining efficiency results obtained from alternative DEA models rather than constructing additional pseudo-models from subsets of the original input and output variables.

For each year t, let $E_{jl}^{(t)}$ denote the efficiency score of DMU_j under DEA model l, where

$$j = 1, 2, \ldots, n, \qquad n = 11, \tag{22}$$

and

$$l = 1, 2, 3, \tag{23}$$

with

$$M_1 = \text{CRS}, \qquad M_2 = \text{IVRS}, \qquad M_3 = \text{OVRS}. \tag{24}$$

The efficiency scores in each DEA-model column are first normalized across the eleven DMUs as

$$p_{jl}^{(t)} = \frac{E_{jl}^{(t)}}{\sum_{j=1}^{n} E_{jl}^{(t)}}, \qquad j = 1, 2, \ldots, n, \quad l = 1, 2, 3. \tag{25}$$

For each DEA model, the normalized values satisfy

$$\sum_{j=1}^{n} p_{jl}^{(t)} = 1. \tag{26}$$

The Shannon entropy associated with model l in year t is then computed as

$$e_l^{(t)} = -\frac{1}{\ln n} \sum_{j=1}^{n} p_{jl}^{(t)} \ln\left(p_{jl}^{(t)}\right), \qquad l = 1, 2, 3, \tag{27}$$

where

$$0 \le e_l^{(t)} \le 1. \tag{28}$$

If $p_{jl}^{(t)} = 0$, the quantity $p_{jl}^{(t)} \ln\left(p_{jl}^{(t)}\right)$ is defined as zero.

The entropy value reflects the degree of uniformity in the efficiency scores produced by a particular DEA specification. A relatively high entropy value indicates that the efficiency scores are more similar across the DMUs and therefore contain less discriminatory information. Conversely, a lower entropy value indicates greater dispersion among the efficiency scores and hence greater discriminatory information.

The degree of diversification of DEA model l is defined as

$$d_l^{(t)} = 1 - e_l^{(t)}. \tag{29}$$

The corresponding Shannon weight is obtained by normalizing the diversification values:

$$w_l^{(t)} = \frac{d_l^{(t)}}{\sum_{h=1}^{3} d_h^{(t)}}, \qquad l = 1, 2, 3. \tag{30}$$

The resulting weights satisfy

$$\sum_{l=1}^{3} w_l^{(t)} = 1, \qquad w_l^{(t)} \ge 0. \tag{31}$$

Accordingly, the annual model weights are denoted by

$$w_{\text{CRS}}^{(t)}, \qquad w_{\text{IVRS}}^{(t)}, \qquad w_{\text{OVRS}}^{(t)}. \tag{32}$$

These weights represent the relative informational contribution of the three DEA efficiency models in a given year. Importantly, the Shannon weights are derived from the distributions of the DEA efficiency results and not directly from the original input and output variables.

The composite Shannon Efficiency Score for DMU_j in year t is then obtained as

$$SES_j^{(t)} = \sum_{l=1}^{3} w_l^{(t)} E_{jl}^{(t)}. \tag{33}$$

Equivalently,

$$SES_j^{(t)} = w_{\mathrm{CRS}}^{(t)} E_{j,\mathrm{CRS}}^{(t)} + w_{\mathrm{IVRS}}^{(t)} E_{j,\mathrm{IVRS}}^{(t)} + w_{\mathrm{OVRS}}^{(t)} E_{j,\mathrm{OVRS}}^{(t)}. \tag{34}$$

A higher value of $SES_j^{(t)}$ indicates stronger overall relative performance after the information contained in the three DEA specifications has been combined. For each year, the eleven DisCos are ranked in descending order of their composite SES values. Where identical SES values occur, average ranks are assigned.

The complete procedure is performed independently for each year from 2018 to 2025. Consequently, the entropy values, diversification measures, Shannon weights, composite SES values, and final rankings are year-specific. This allows changes in the discriminatory contribution of CRS, IVRS, and OVRS to be reflected in the annual efficiency assessment.

The annual Shannon model weights are reported in the Results section, together with the corresponding composite SES values and rankings. The rankings generated directly by CRS, IVRS, and OVRS are subsequently compared using Spearman's rank correlation coefficient to assess the degree of agreement among the three DEA specifications.

The integration of the input-oriented CRS and IVRS specifications and the output-oriented OVRS specification with Shannon entropy provides a systematic framework for combining complementary DEA efficiency perspectives. Related applications and methodological developments in DEA–Shannon entropy integration are discussed in [33–35].

The methodological framework adopted in this study is summarized in Figure 1. The figure illustrates how the annual data for the eleven Nigerian electricity distribution companies are first evaluated under the CRS, IVRS, and OVRS DEA models, after which the resulting efficiency scores are combined into a DEA efficiency matrix and aggregated using Shannon entropy to obtain the composite Shannon Efficiency Score.

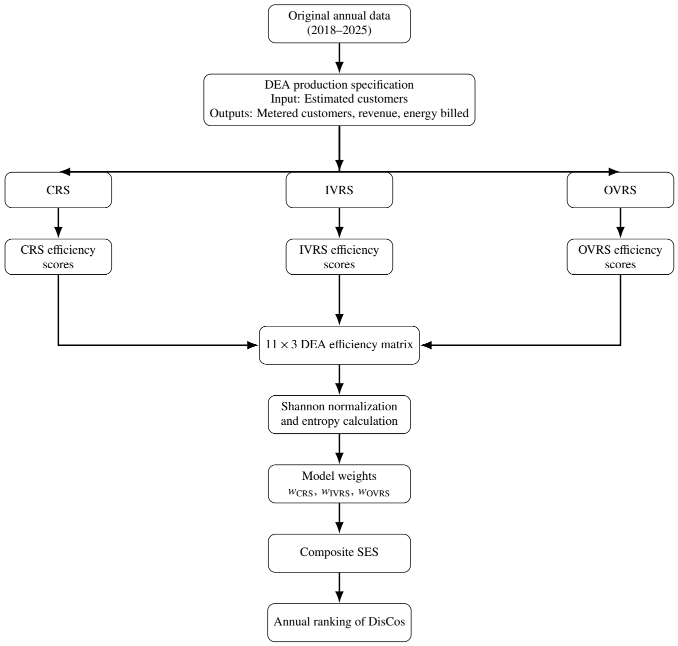


Figure 1: Flowchart of the DEA–Shannon entropy integration procedure.

5. Results and discussion

The relative efficiency of the eleven legacy Nigerian electricity distribution companies was evaluated annually over the period 2018–2025 using the revised DEA specification. Three complementary DEA models were employed: constant returns to scale (CRS), input-oriented variable returns to scale (IVRS), and output-oriented variable returns to scale (OVRS). The resulting efficiency scores are presented in Tables 3–5, respectively. These results provide separate assessments of overall technical efficiency, pure technical efficiency, and output-oriented performance under variable returns to scale.

Following the conventional DEA analysis, the annual CRS, IVRS, and OVRS efficiency results were integrated using the Shannon entropy procedure. For each year, the three DEA efficiency-score columns were normalized, their entropy and diversification measures were calculated, and year-specific Shannon weights were obtained. These weights were then used to aggregate the three DEA efficiency measures into a composite Shannon Efficiency Score (SES) for each DisCo. The annual Shannon model weights and the corresponding numerical SES values are reported in Tables 7 and 8, respectively, while the resulting ranking patterns are illustrated in Figure 2. The annual Spearman rank correlations among the CRS, IVRS, and OVRS rankings are reported in Table 9.

The discussion proceeds by first comparing the CRS and IVRS results to distinguish overall technical inefficiency from scale-related effects. The OVRS results are then examined to assess the potential for proportional expansion of desirable outputs at observed input levels. Thereafter, the Shannon entropy weights, composite SES values, and resulting rankings are analysed to provide an integrated assessment of relative performance. Finally, Spearman's rank correlation analysis is used to examine the degree of agreement among the annual rankings generated by the CRS, IVRS, and OVRS specifications.

5.1. *Comparison between CRS and IVRS results*

A comparison of the CRS and IVRS efficiency scores reveals important differences in the relative performance of the Nigerian electricity distribution companies over the period 2018–2025. The CRS model measures overall technical efficiency under the assumption of constant returns to scale, whereas the IVRS model measures input-oriented pure technical efficiency under variable returns to scale. Comparing the two therefore provides a basis for distinguishing inefficiency associated with operational performance from inefficiency associated with scale.

In general, the IVRS efficiency scores are greater than or equal to the corresponding CRS efficiency scores. This relationship is consistent with DEA theory. The VRS model introduces

Table 3: Efficiency scores under the constant returns to scale (CRS) model, 2018–2025.

DMUs	2018	2019	2020	2021	2022	2023	2024	2025
AEDC	0.7319	0.8168	0.9045	0.5726	0.5260	0.3729	0.9200	0.5516
BEDC	0.9827	0.8797	0.8639	0.4140	0.3887	0.2373	0.2845	0.1825
EKEDC	1.0000	1.0000	1.0000	0.7433	0.8064	0.6672	0.8858	1.0000
EEDC	0.4481	0.4607	0.4708	0.2672	0.2817	0.2083	0.2663	0.1678
IBEDC	0.3757	0.3281	0.4041	0.2071	0.2551	0.1858	0.2222	0.1694
IKEDC	0.6881	0.8492	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JEDC	0.3163	0.3500	0.1774	0.1522	0.1744	0.1456	0.1400	0.0729
KDEDC	0.3061	0.2590	0.2366	0.1537	0.2051	0.1179	0.1033	0.0853
KEDC	0.3942	0.3683	0.2453	0.1780	0.2129	0.1756	0.1351	0.0878
PHEDC	1.0000	1.0000	0.8047	0.4416	0.5882	0.5230	0.2300	0.2813
YEDC	0.2157	0.2106	0.1817	0.0789	0.0896	0.0443	0.0727	0.0703

Table 4: Efficiency scores under the input-oriented variable returns to scale (IVRS) model, 2018–2025.

DMUs	2018	2019	2020	2021	2022	2023	2024	2025
AEDC	1.0000	1.0000	1.0000	0.5867	0.5289	0.3891	0.9986	0.5536
BEDC	1.0000	1.0000	0.8811	0.4783	0.4779	0.3217	0.3846	0.1886
EKEDC	1.0000	1.0000	1.0000	0.9313	1.0000	0.8505	1.0000	1.0000
EEDC	0.4612	0.4999	0.4993	0.3416	0.3930	0.3068	0.3810	0.1702
IBEDC	1.0000	1.0000	0.4318	1.0000	1.0000	1.0000	1.0000	1.0000
IKEDC	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JEDC	0.5606	0.6483	0.5083	0.5193	0.5613	0.4435	0.4432	0.1615
KDEDC	0.4484	0.4370	0.4692	0.4188	0.4343	0.3423	0.4029	0.2543
KEDC	0.5604	0.6124	0.5087	0.5189	0.5607	0.4734	0.3982	0.1755
PHEDC	1.0000	1.0000	0.9107	0.7853	0.9670	0.9479	0.4140	0.2895
YEDC	0.7000	0.7476	0.7541	0.6309	0.6737	0.3162	0.3822	0.2563

the additional convexity constraint:

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{35}$$

which restricts the feasible reference technology relative to the CRS technology. Consequently, under an input-oriented formulation, the VRS efficiency score cannot be lower than the corresponding CRS efficiency score. Thus,

$$TE_{\text{CRS}} \leq TE_{\text{VRS}}. \tag{36}$$

The difference between these two measures provides an indication of the extent to which scale effects contribute to the overall technical inefficiency of a DMU.

Several distribution companies exhibit substantial differences between their CRS and IVRS efficiency scores. For example, IBEDC records IVRS efficiency scores of 1.0000 in both 2018 and 2019, whereas its corresponding CRS scores are 0.3757 and 0.3281, respectively. Similar differences are observed for IBEDC in several other years. These results indicate that IBEDC can attain high pure technical efficiency when scale effects are separated from the assessment, while its substantially lower CRS scores indicate that scale inefficiency contributes importantly to its overall technical inefficiency.

A similar pattern is observed for several other DisCos. For instance, AEDC records an IVRS efficiency score of 1.0000 in 2018 compared with a CRS score of 0.7319, while BEDC records an IVRS score of 1.0000 and a CRS score of 0.9827 in the same year. PHEDC also exhibits noticeable differences between its CRS and IVRS efficiency scores in several later years. These disparities show that a lower CRS efficiency score does not necessarily imply an equivalent degree of pure technical inefficiency, because part of the observed CRS inefficiency may arise from operating at a non-optimal scale.

In contrast, some DMUs record identical CRS and IVRS efficiency scores in particular years. EKEDC records efficiency scores of 1.0000 under both CRS and IVRS in 2018, 2019, 2020, and 2025. IKEDC similarly records scores of 1.0000 under both specifications from 2020 through 2025, while PHEDC attains full efficiency under both CRS and IVRS in 2018 and 2019. For these DMU-year observations, overall technical efficiency and pure technical efficiency coincide, and the corresponding scale efficiency is equal to one.

To quantify the contribution of scale effects, scale efficiency is defined as:

$$SE = \frac{TE_{\mathrm{CRS}}}{TE_{\mathrm{VRS}}}, \tag{37}$$

where TE_{CRS} denotes technical efficiency under constant returns to scale and TE_{VRS} denotes pure technical efficiency under variable returns to scale. Since

$$TE_{\mathrm{CRS}} \leq TE_{\mathrm{VRS}}, \tag{38}$$

the scale-efficiency measure satisfies

$$0 < SE \leq 1. \tag{39}$$

A value of $SE = 1$ indicates that the DMU is scale efficient, meaning that its CRS and VRS technical-efficiency scores coincide. In contrast, $SE < 1$ indicates the presence of scale inefficiency, with smaller values reflecting a larger difference between overall technical efficiency and pure technical efficiency.

The comparison therefore provides a clearer distinction between pure technical inefficiency and scale inefficiency among the Nigerian DisCos. EKEDC and IKEDC achieve both technical and scale efficiency in several years, whereas IBEDC frequently records high pure technical efficiency together with substantially lower CRS efficiency, indicating an important contribution from scale inefficiency. Other DisCos, including JEDC, KDEDC, KEDC, and YEDC, generally record comparatively lower efficiency scores under both CRS and IVRS in several years. For these companies, the observed performance differences cannot be explained by scale effects alone, since limitations in pure technical efficiency are also evident from the IVRS results.

The efficiencies assessed using the OVRS model are presented in Table 5. The results complement the CRS and IVRS findings reported in Tables 3 and 4 by showing the extent to which each DisCo could proportionally expand its desirable outputs while maintaining the observed input level. Several DisCos attain an efficiency score of 1.0000 in particular years, indicating relative efficiency under the output-oriented variable returns to scale specification, whereas others exhibit varying degrees of output inefficiency. The occurrence of multiple efficient DMUs under the conventional DEA models also illustrates the difficulty of obtaining a unique overall ranking from the individual DEA specifications alone.

Table 6 reports the scale-efficiency scores computed as the ratio of CRS technical efficiency to VRS pure technical efficiency. Considerable heterogeneity is observed across the DisCos and over time. A scale-efficiency score of 1.0000 indicates that the CRS and VRS efficiency scores coincide, implying scale efficiency for that DMU-year observation.

EKEDC records scale efficiency of 1.0000 in 2018, 2019, 2020, and 2025, while IKEDC is scale efficient continuously from 2020 to 2025. PHEDC also records scale efficiency of 1.0000 in 2018 and 2019. In contrast, IBEDC records substantially lower scale-efficiency scores in several years, particularly from 2021 onward, indicating that a considerable portion of its CRS inefficiency is attributable to scale effects. Similarly, JEDC, KDEDC, KEDC, and YEDC generally exhibit relatively low scale-efficiency values over much of the study period.

The results therefore confirm that scale effects differ substantially across the Nigerian DisCos and across years. Some companies operate at or close to the most productive scale size in particular periods, whereas others exhibit persistent scale inefficiency. These findings complement the CRS and IVRS results by separating the scale component of overall technical inefficiency from pure technical inefficiency.

To address this limitation, the CRS, IVRS, and OVRS efficiency results are integrated using the Shannon entropy procedure to obtain a single composite Shannon Efficiency Score (SES) for each DisCo in each year. The corresponding annual SES values and ranks are reported in Table 8, while the resulting composite ranking trajectories are illustrated in Figure 2.

The annual composite SES rankings of the eleven Nigerian electricity distribution companies are illustrated in Figure 2(a)–(k). AEDC shows a generally strong but fluctuating ranking pattern, moving from fourth position in 2018 to second position in 2024 before settling at third position in 2025, as shown in Figure 2a. BEDC performs relatively well in the early years, ranking third in both 2018 and 2019, but gradually declines to seventh position by 2025, as presented in Figure 2b. EKEDC exhibits consistently strong performance throughout the study period, remaining between first and third positions and sharing the highest rank in several years, as shown in Figure 2c.

EEDC displays a comparatively stable middle-to-lower ranking pattern, occupying seventh position from 2018 to 2023 before improving slightly to sixth position in 2024 and 2025, as illustrated in Figure 2d. IBEDC shows a gradual improvement in its relative position, moving from sixth position during 2018–2020 to fourth position from 2023 onward, as shown in Figure 2e. IKEDC records one of the strongest upward trajectories, improving from fifth position in 2018 to first position from 2021 through 2024, while sharing the highest rank in 2020 and 2025, as presented in Figure 2f.

In contrast, JEDC remains among the lower-ranked DisCos, fluctuating between eighth and eleventh positions over the study period, as shown in Figure 2g. KDEDC also occupies predominantly lower positions, generally ranging between eighth and tenth place, as illustrated in Figure 2h. KEDC exhibits a relatively stable trajectory, remaining around eighth and ninth positions across most years, as presented in Figure 2i. PHEDC shows a markedly different pattern: it shares the highest rank in 2018 and 2019 but subsequently declines, reaching seventh position in 2024 before improving to fifth position in 2025, as shown in Figure 2j. YEDC consistently records one of the weakest composite performances, remaining in tenth or eleventh position throughout the period, as illustrated in Figure 2k.

Overall, the trajectories in Figure 2(a)–(k) reveal substantial heterogeneity in relative performance across the eleven DisCos. EKEDC and IKEDC are among the most consistently high-ranking companies over the study period, while JEDC, KDEDC, KEDC, and particularly YEDC remain concentrated toward the lower end of the composite ranking distribution. These patterns reflect the combined information contained in the CRS,

Table 5: Efficiencies of DMUs obtained using the output-oriented variable returns to scale (OVRS) model for 2018–2025.

DMUs	2018	2019	2020	2021	2022	2023	2024	2025
AEDC	1.0000	1.0000	1.0000	0.9619	0.9505	0.9127	0.9871	0.9200
BEDC	1.0000	1.0000	0.8799	0.8465	0.7565	0.6940	0.6773	0.5972
EKEDC	1.0000	1.0000	1.0000	0.7981	1.0000	0.7845	1.0000	1.0000
EEDC	0.7156	0.7024	0.6701	0.7523	0.6468	0.6333	0.6368	0.6973
IBEDC	1.0000	1.0000	0.9821	1.0000	1.0000	1.0000	1.0000	1.0000
IKEDC	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JEDC	0.3787	0.3907	0.2258	0.2877	0.2859	0.3283	0.2959	0.2780
KDEDC	0.5055	0.4600	0.3832	0.3670	0.4502	0.3443	0.2402	0.2691
KEDC	0.5460	0.5052	0.3759	0.3430	0.3621	0.3708	0.3180	0.3474
PHEDC	1.0000	1.0000	0.8824	0.5592	0.6309	0.5507	0.5012	0.5859
YEDC	0.2304	0.2247	0.2088	0.1250	0.1242	0.1387	0.1784	0.1516

Table 6: Scale efficiency of the Nigerian electricity distribution companies, 2018–2025.

DMU	2018	2019	2020	2021	2022	2023	2024	2025
AEDC	0.7319	0.8168	0.9045	0.9760	0.9945	0.9584	0.9213	0.9964
BEDC	0.9827	0.8797	0.9805	0.8656	0.8134	0.7376	0.7397	0.9677
EKEDC	1.0000	1.0000	1.0000	0.7981	0.8064	0.7845	0.8858	1.0000
EEDC	0.9716	0.9216	0.9429	0.7822	0.7168	0.6789	0.6990	0.9859
IBEDC	0.3757	0.3281	0.9358	0.2071	0.2551	0.1858	0.2222	0.1694
IKEDC	0.6881	0.8492	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
JEDC	0.5642	0.5399	0.3490	0.2931	0.3107	0.3283	0.3159	0.4514
KDEDC	0.6826	0.5927	0.5043	0.3670	0.4723	0.3444	0.2564	0.3354
KEDC	0.7034	0.6014	0.4822	0.3430	0.3797	0.3709	0.3393	0.5003
PHEDC	1.0000	1.0000	0.8836	0.5623	0.6083	0.5517	0.5556	0.9717
YEDC	0.3081	0.2817	0.2409	0.1251	0.1330	0.1401	0.1902	0.2743

Table 7: Annual Shannon entropy weights assigned to the CRS, IVRS, and OVRS models, 2018–2025.

Year	CRS	IVRS	OVRS
2018	0.4927	0.1868	0.3205
2019	0.5174	0.1509	0.3317
2020	0.5080	0.1497	0.3423
2021	0.5666	0.1368	0.2966
2022	0.5382	0.1509	0.3109
2023	0.5639	0.2196	0.2165
2024	0.5902	0.1733	0.2366
2025	0.5262	0.3122	0.1616

IVRS, and OVRS efficiency measures through the year-specific Shannon entropy weights.

The annual Shannon entropy weights assigned to the CRS, IVRS, and OVRS efficiency models are presented in Table 7. The weights vary across years because they are derived independently from the annual distributions of the corresponding DEA efficiency scores.

As shown in Table 7, the CRS model receives the largest Shannon weight in every year of the study period, ranging from 0.4927 in 2018 to 0.5902 in 2024. The IVRS and OVRS weights exhibit greater year-to-year variation, reflecting differences in the discriminatory information contained in their respective efficiency-score distributions. Since the three weights sum to unity for each year, they represent the relative contributions of the three DEA specifications to the computation of the composite Shannon Efficiency Score (SES).

The composite Shannon Efficiency Scores obtained by combining the CRS, IVRS, and OVRS efficiency results using the year-specific Shannon weights are reported in Table 8, together with the corresponding annual ranks. The results indicate that the relative positions of the DisCos vary over time and that no single company dominates the entire study period. EKEDC and IKEDC frequently appear among the higher-performing DisCos, with both attaining composite SES values of 1.0000 in several years. PHEDC also records a composite SES of 1.0000 in 2018 and 2019, but its relative position declines in several subsequent years. AEDC generally remains within the upper part of the ranking distribution, although its composite SES varies

Table 8: Composite Shannon Efficiency Scores (SES) and annual ranks of the Nigerian DisCos, 2018–2025.

DMU	2018	2019	2020	2021	2022	2023	2024	2025
AEDC	0.8679 (4)	0.9052 (5)	0.9515 (3)	0.6900 (3)	0.6584 (4)	0.4933 (5)	0.9495 (2)	0.6118 (3)
BEDC	0.9915 (3)	0.9378 (3)	0.8720 (4)	0.5511 (4)	0.5165 (6)	0.3547 (6)	0.3948 (5)	0.2514 (7)
EKEDC	1.0000 (1.5)	1.0000 (1.5)	1.0000 (1.5)	0.7853 (2)	0.8958 (2)	0.7328 (2)	0.9326 (3)	1.0000 (1.5)
EEDC	0.5363 (7)	0.5468 (7)	0.5433 (7)	0.4213 (7)	0.4120 (7)	0.3219 (7)	0.3738 (6)	0.2541 (6)
IBEDC	0.6924 (6)	0.6524 (6)	0.6061 (6)	0.5507 (5)	0.5991 (5)	0.5409 (4)	0.5410 (4)	0.5629 (4)
IKEDC	0.8463 (5)	0.9220 (4)	1.0000 (1.5)	1.0000 (1)	1.0000 (1)	1.0000 (1)	1.0000 (1)	1.0000 (1.5)
JEDC	0.3819 (10)	0.4085 (9)	0.2435 (11)	0.2426 (10)	0.2674 (10)	0.2506 (9)	0.2294 (8)	0.1337 (11)
KDEDC	0.3966 (9)	0.3525 (10)	0.3216 (9)	0.2532 (9)	0.3159 (8)	0.2162 (10)	0.1876 (10)	0.1678 (8)
KEDC	0.4739 (8)	0.4505 (8)	0.3294 (8)	0.2736 (8)	0.3118 (9)	0.2833 (8)	0.2240 (9)	0.1571 (9)
PHEDC	1.0000 (1.5)	1.0000 (1.5)	0.8472 (5)	0.5235 (6)	0.6586 (3)	0.6223 (3)	0.3260 (7)	0.3331 (5)
YEDC	0.3109 (11)	0.2963 (11)	0.2767 (10)	0.1681 (11)	0.1885 (11)	0.1244 (11)	0.1513 (11)	0.1415 (10)

Table 9: Annual Spearman rank correlations among the CRS, IVRS, and OVRS rankings of the eleven Nigerian DisCos, 2018–2025.

Year	CRS–IVRS	CRS–OVRS	IVRS–OVRS
2018	0.661	0.830	0.816
2019	0.616	0.765	0.816
2020	0.745	0.910	0.574
2021	0.419	0.765	0.443
2022	0.367	0.798	0.417
2023	0.510	0.756	0.543
2024	0.486	0.835	0.685
2025	0.690	0.846	0.667

Note: For each year, the eleven DisCos were ranked separately under the CRS, IVRS, and OVRS specifications in descending order of their efficiency scores. Average ranks were assigned where ties occurred. Spearman's rank correlation coefficient was then calculated cross-sectionally between each pair of annual rank vectors.

across the study period.

In contrast, JEDC, KDEDC, KEDC, and YEDC generally occupy lower positions in the annual composite rankings. YEDC records particularly low SES values throughout most of the study period, while JEDC also remains among the lower-ranked DisCos in several years. The observed variation in the composite SES reflects changes in both the underlying DEA efficiency scores and the year-specific Shannon weights assigned to the CRS, IVRS, and OVRS models. The resulting composite ranking therefore represents an integrated assessment of the information provided by the three DEA specifications rather than the outcome of any single DEA model. The corresponding annual composite ranking trajectories are illustrated in Figure 2(a)–(k).

5.2. Rank-correlation analysis

To assess the degree of agreement among the annual rankings generated by the CRS, IVRS, and OVRS DEA specifications, Spearman's rank correlation coefficient was calculated cross-sectionally across the eleven DisCos for each year from 2018 to 2025 as shown in Table 9. This approach evaluates whether the alternative DEA models produce similar relative rankings of the distribution companies within the same year.

For each year t, the eleven DisCos were ranked separately according to their CRS, IVRS, and OVRS efficiency scores. Higher efficiency scores were assigned better ranks, and average ranks were used where ties occurred. The resulting annual rank vectors may be written as

$$\mathbf{R}_t^{(M)} = \left(R_{1,t}^{(M)}, R_{2,t}^{(M)}, \ldots, R_{11,t}^{(M)}\right), \tag{40}$$

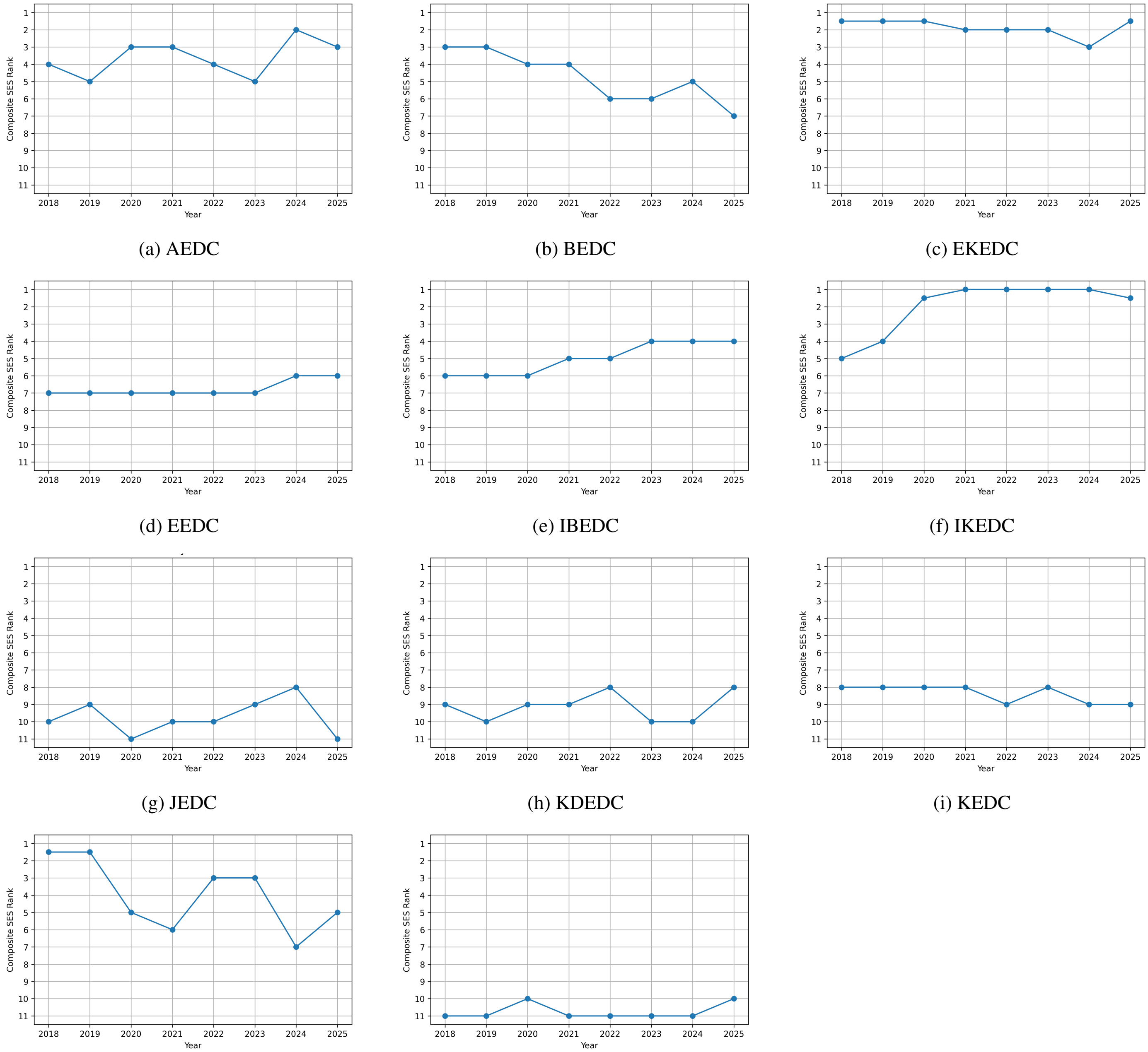
where

$$M \in \{\mathrm{CRS}, \mathrm{IVRS}, \mathrm{OVRS}\}. \tag{41}$$

For each year, pairwise Spearman rank correlations were then calculated between the CRS and IVRS rank vectors, the CRS and OVRS rank vectors, and the IVRS and OVRS rank vectors. Spearman's coefficient satisfies:

$$-1 \leq \rho_s \leq 1. \tag{42}$$

A value of ρ_s close to +1 indicates strong agreement between the rankings produced by two DEA specifications, a value close to 0 indicates weak monotonic agreement, and a value close to −1 indicates strong disagreement.



(a) AEDC (b) BEDC (c) EKEDC

(d) EEDC (e) IBEDC (f) IKEDC

(g) JEDC (h) KDEDC (i) KEDC

(j) PHEDC (k) YEDC

Figure 2: Annual rankings of the eleven Nigerian electricity distribution companies based on the composite Shannon Efficiency Score (SES), 2018–2025.

The Spearman rank-correlation results in Table 9 show that the degree of agreement among the CRS, IVRS, and OVRS rankings varies across years. All reported coefficients are positive, indicating that the alternative DEA specifications generally produce rankings that move in the same direction, although the strength of agreement differs across model pairs and years.

The CRS–OVRS correlations exhibit the strongest and most consistent agreement over the study period, ranging from 0.756 to 0.910. The highest CRS–OVRS correlation occurs in 2020, with $\rho_s = 0.910$, indicating a very strong similarity between the rankings produced by the two specifications in that year. The CRS–IVRS correlations are positive throughout the period but show greater variation, ranging from 0.367 in 2022 to 0.745 in 2020.

The IVRS–OVRS correlations also remain positive across all years, ranging from 0.417 to 0.816. The strongest IVRS–OVRS agreement is observed in 2018 and 2019, while weaker agreement is observed in some later years, particularly 2022. These variations indicate that the three DEA specifications share common ranking information but do not produce identical annual orderings of the eleven DisCos.

Overall, the cross-sectional correlation results confirm that the CRS, IVRS, and OVRS models provide related but not interchangeable perspectives on relative efficiency. This variation in annual ranking agreement further supports the use of the Shannon entropy aggregation procedure to combine the information contained in the three DEA specifications into a single composite Shannon Efficiency Score.

6. Conclusion

This study evaluated the relative operational efficiency of the eleven legacy Nigerian electricity distribution companies over the period 2018–2025 using an integrated Data Envelopment Analysis (DEA)–Shannon entropy framework. Three complementary DEA specifications were estimated annually: constant returns to scale (CRS), input-oriented variable returns to scale (IVRS), and output-oriented variable returns to scale (OVRS). The resulting efficiency scores were subsequently combined using year-specific Shannon entropy weights to construct a composite Shannon Efficiency Score (SES) for each DisCo.

The findings reveal substantial heterogeneity in relative performance across the DisCos and over time. Differences between the CRS and IVRS scores show that scale effects contribute to the overall inefficiency of several companies, while the calculated scale-efficiency values further demonstrate substantial variation in operating scale across DisCos and years. The OVRS results provide an additional perspective on the potential for proportional expansion of the desirable outputs at the observed input level. The three DEA specifications therefore provide complementary rather than interchangeable assessments of relative operational performance.

The cross-sectional Spearman rank-correlation analysis also shows that the degree of agreement among the CRS, IVRS, and OVRS rankings varies across years. Although the three specifications generally produce positively associated rankings, the strength of agreement differs by model pair and year. This variation confirms that the alternative DEA specifications contain related but distinct ranking information.

The composite SES results provide an integrated summary of these alternative DEA efficiency perspectives. IKEDC and EKEDC generally emerge among the stronger-performing DisCos over much of the study period, although their relative positions vary across years. PHEDC performs strongly during the earlier part of the study period but records weaker relative positions in several later years, while AEDC generally remains within the upper part of the composite ranking distribution.

In contrast, JEDC, KDEDC, KEDC, and YEDC frequently occupy lower positions in the annual SES rankings. These results should be interpreted as measures of relative efficiency within the annual DEA reference set and not as evidence of statistically significant or causal effects.

Metering performance forms an explicit component of the DEA production specification adopted in this study. The number of metered customers is treated as a desirable output, whereas the number of customers remaining under estimated billing is represented as the input-side operating burden. Energy billed, measured in gigawatt-hours (GWh), and revenue collected are also treated as desirable outputs. Consequently, the resulting efficiency scores inherently reflect differences in these operational characteristics across the DisCos.

The present DEA results therefore do not constitute an independent empirical test of an association between metering performance and operational efficiency. Any such relationship would require a separate statistical, econometric, or causal-inference analysis in which metering indicators are evaluated independently of the construction of the DEA efficiency scores.

Overall, the integrated DEA–Shannon entropy framework provides a transparent and reproducible approach for benchmarking the relative performance of Nigerian electricity distribution companies while combining the complementary information generated by alternative DEA specifications. Shannon entropy does not modify the CRS, IVRS, or OVRS production frontiers and does not increase the discriminatory power of the individual DEA models. Instead, it derives information-based weights from the annual distributions of the three DEA efficiency scores and uses these weights to construct a single composite SES. Any additional differentiation among the DisCos therefore arises at the composite aggregation and ranking stage rather than within the underlying DEA models themselves.

Future research may extend the present analysis by incorporating additional operational and structural variables such as distribution losses, number of employees, network characteristics, customer categories, service-quality indicators, and disaggregated revenue measures. Further studies may also employ regression-based, econometric, or causal-inference techniques to investigate independently whether metering performance, energy billed, revenue, network conditions, and other operational factors are statistically associated with, or exert causal effects on, distribution-company efficiency.

Data availability

The data used in this study were obtained from publicly available electricity-sector publications and datasets of the National Bureau of Statistics and the Nigerian Electricity Regulatory Commission. The complete harmonized annual dataset used in the DEA analysis is provided in Supplementary Table S1, while Supplementary Table S2 documents the corresponding source mapping and annualization procedures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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