TECHNICAL EFFICIENCY AMONG ELECTRICITY GENERATING FIRMS IN UGANDA

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Abstract

Inefficiencies in Uganda's electricity sector, where high tariffs and low access persist despite surplus capacity has grown concerns to the researchers. This study aims to fill the policy and research gap by evaluating firm-level technical efficiency to support sustainable, affordable, and reliable electricity. Using secondary data from the Electricity Regulatory Authority (2016-2023), the study analyzes 36 generating firms through an input-oriented Data Envelopment Analysis (DEA) model and Tobit regression. Results show that only 22% of the firms operate efficiently, while 67% perform below 50% efficiently, mainly due to outdated technology, high operational costs, and regulatory barriers. Larger plants tend to be more efficient, while high workforce size and O&M costs reduce efficiency. One key recommendations is for policy makers to introduce performance-based regulations and incentives for firms that adopt modern technology. The study contributes new evidence by applying DEA in the developing country context and offering firm-level insights into supply-side electricity efficiency, an area that remains underexplored.

Key words: Technical Efficiency, Tobit Regression, & Data Envelopment Analysis (DEA)

1.0 Introduction

Energy plays a pivotal role in promoting socioeconomic transformation and sustainable development, as reflected in global development frameworks such as Sustainable Development Goal 7 (SDG 7), which emphasizes access to affordable, reliable, and modern energy for all. Over the past decades, rising global energy demand, particularly in developing countries, has necessitated the expansion of electricity generated to meet growing consumption needs. However, achieving universal access to energy is not merely a function of increasing supply; it also depends on ensuring affordable, reliable, and sustainability, all of which are closely tied to the cost-efficiency of electricity generation.

A major challenge, however, is that electricity costs remain high in many countries despite surplus generation capacity. This contradiction suggests that structural and operational inefficiencies persist in electricity generation systems. Energy efficiency is increasingly recognized as a crucial factor in improving electricity sector performance and achieving sustainability goals in developing countries. Studies have shown that implementing energy efficiency measures can lead to significant energy savings, reduced peak demand, and increased energy access (Pudleiner et al., 2017). Also, energy efficiency improvements are estimated to potentially deliver over a third of the necessary greenhouse gas emission reductions for climate stabilization (Fowlie & Meeks, 2020). Efficient electricity generation also contributes to reduced dependence on fossil fuels and decreased greenhouse gas emissions (Rodriquez-Lozano & Cifuentes-Yate, 2021; Pinto et al., 2023).

Globally, the technical efficiency of electricity generation has been widely studied using models like Data Envelopment Analysis (DEA). For instance, Dogan and Tugcu (2015) found significant differences in efficiency across G-20 countries, with China and Russia outperforming their counterparts. Similarly, Rodriguez-Lozano and Cifuentes-Yate (2021) revealed global efficiency levels typically ranging from 60% to 90%. However, despite global improvements in primary-to-final energy conversion, end-use efficiency has remained stagnant, and inefficiencies at the generation level persist (Pinto et al., 2023). This points to a global problem of slow progress in generation efficiency, which could undermine broader climate and development targets.

In Sub-Saharan Africa (SSA), these inefficiencies are even more pronounced. Despite major energy sector reforms and capacity investments, the region continues to suffer from low electrification rates, frequent power outages, high technical losses, and poor infrastructure (Agoundedemba et al., 2023; Asantewea et al., 2022). A significant regional gap is the limited integration of renewable energy and underutilization of local energy resources, such as biomass (Jingura & Kamusoko, 2017). In East Africa specially, technical performance gaps of up to 20% have been observed in electricity systems, attributed to excess input use and output shortfalls (René, 2022). These inefficiencies are not only operational but also institutional and structural, with limited incentives for performance improvement.

Uganda, like many Sub-Saharan Africa, illustrates this paradox. Despite an installation generation capacity of 1,346.6 MW and a peak demand of only 785 MW, leaving a substantial surplus of 562 MW, electricity tariffs remain among the highest in the region (MoEMD, 2023). This raises critical concerns about inefficiencies in the electricity generation process. Moreover, Uganda's electricity access rate remains at 55%, far below the regional average for developing countries. This suggests that excess capacity is not translating into improved access or lower prices, possibly due to high generation costs, technical losses, or scale inefficiencies. Policy responses have also been inadequate. While Uganda's 2023 National Energy Policy and Draft Energy Efficiency and Conservation Bill aim to improve energy efficiency, they focus almost exclusively on demand-side interventions (e.g. in households, industry, transport), with limited attention to the generation side. This represents a significant policy gap, as generation inefficiencies directly affect the affordability and reliability of power supply.

Academically, most efficiency studies in the energy sector have also focused on consumption, environmental impacts or national-level trends. There is a lack of firm-level analysis, especially in developing countries and within the supply side of electricity sector. Studies such as those by Wasseh et al. (2023) and Hou et al. (2022) highlight efficiency patterns at a broad level but provided limited insights into the operational dynamics of individual electricity-generating firms. As such, firm-level inefficiencies remain poorly understood in countries like Uganda, impending targeted reforms.

To fill these theoretical, empirical, and policy gaps, this study adopts a robust framework combining Efficiency Measurement Theory (Charnes et al., 1978) and Scale Efficiency Theory (Banker, 1984) with DEA. This integration enables the evaluation of both technical and scale efficiency, offering deeper insights into performance variations among electricity-generating firms. Technical efficiency at the generation level is often influenced by multiple factors, including fuel type, plant size, ownership structure, age of the facility, technology innovation, and managerial practices (Nguyen et al., 2022; Benini & Cattani, 2022; Hou et al., 2022). Operational constraints such as inputs shortages, maintenance delays, and regulatory inefficiencies also significantly affect generation performance (Sengupta & Mukherjee, 2022; Bernstein, 2020).

Therefore, the objective of this study is to evaluate the technical efficiency of electricity-generating firms in Uganda and to identify the key drivers influencing their performance. By focusing on firm-level analysis within a developing country context, the study contributes to the underexplored domain of supply-side electricity efficiency and offers evidence-based policy guidance to enhance the sustainability, affordability, and reliability of Uganda's electricity sector

2.0 Literature Review

This chapter explore the theoretical and empirical literature review on technical efficiency, to have the ground understanding of the concept and identify the gaps in available literature.

2.1 Theoretical Review

The Efficiency Measurement Theory, introduced by Charnes et al. (1978), and further explained in a study by Cook & Seiford (2009), provides a non-parametric framework for assessing the relative efficiency of decision-making units (DMUs) by comparing weighted outputs to weighted inputs. It constructs an efficiency frontier defined by the most efficient units, assigning objectives weights based on observed data. While the model is flexible and widely applied across sectors due to its ability to handle multiple inputs and outputs, it does not separate technical efficiency from scale inefficiency, meaning a unit might appear inefficient due to operating at an inappropriate scale rather than poor resource use.

The Scale efficiency theory, developed by Banker (1984), and elaborated by Banker and Thrall (1992), suggests that a decision-making unit (DMU) can enhance productivity by operating at its most productive scale size. Integrating into Data Envelopment Analysis (DEA), this theory distinguishes between increasing, constant, or decreasing returns to scale, helping assess whether inefficiency stems from scale mismatches. In the energy sector, it aids in identifying optimal plant sizes and efficient resources use, thereby informing cost-effective and sustainable infrastructure planning. The theory has been widely applied and explained by scholars such as Fare et al. (1985), Banker et al. (1984), Cooper et al. (2006), and Bernstein (2020).

The strength of this theory is rooted in the ability to identify the optimal scale of operation, allowing firms to maximize output without overextending resources of facing diminishing returns, and its ability to distinguish between technical efficiency and scale efficiency, enabling firms to understand whether inefficiencies are due to size of operation or the way processes are managed. However, it is very sensitive to outliers in the data set

2.2 Empirical Review of literature

Recent studies have identified several key factors influencing technical efficiency in electricity generation, including firm ownership, plant age, and investment in infrastructure. State-owned enterprises typically show lower efficiency compared to private firms, and plant age can negatively impact performance, as observed in Kenya's thermal power plants (Njeru et al., 2020). Grid connection, deregulation, and private sector involvement have been linked to improved efficiency and productivity (Nguyen et al., 2022; René, 2022). Technological advancements, such as investments in modern equipment, higher wages for employees, and the adoption of systems like supercritical turbines, have also played a crucial role in enhancing energy efficiency and reducing emissions, as seen in research from India (Murty & Nagpal, 2020) and Europe (Tillman, 2015).

Despite these improvements, there are significant gaps in understanding technical efficiency, particularly in low-income and conflict-affected regions like sub-Saharan Africa, where limited infrastructure and regulatory challenges hinder progress. Most existing research has focused on manufacturing and consumer-side efficiency, with less attention given to electricity-generating firms (supply side). Addressing these gaps could provide valuable insights into optimizing technical efficiency in electricity generation, ensuring better energy access, and promoting sustainable, affordable energy solutions in these underserved regions, such as Uganda, where the electricity sector is still developing.

The number of employees and maintenance costs are key operational factors that influence the efficiency of electricity-generating firms. Research in the Portuguese electricity sector found that moderate working hours and competitive wages, which are closely tied to labor management and maintenance-related expenditures, contribute positively to technical efficiency (Hou et al., 2022). While a sufficient workforce is essential for maintaining operational reliability and minimizing downtime, excessive staffing or poor labor utilization can lead to inefficiencies. Similarly, studies emphasize that appropriate allocation of maintenance costs, particularly when aligned with proactive, leadership-driven maintenance strategies, enhances power plant performance (Wai Foon & Terziovski, 2014). Evidence from Kenyan thermal power plants further supports this, revealing that firms with effective maintenance and operational practices achieve higher efficiency scores, whereas inefficiencies are often linked to underutilized human resources and outdated systems (Njeru et al., 2020). These findings underscore the importance of balancing employee numbers and maintenance investments to optimize firm-level efficiency.

Operation and maintenance (O&M) costs significantly influence the efficiency of electricity-generating firms. Effective O&M practices, such as committed leadership, regular maintenance, and adequate investment in infrastructure, have been shown to improve technical efficiency (Wai Foon & Terziovski, 2014; Hou et al., 2022). Conversely, factors like aging infrastructure and public ownership are associated with lower efficiency, while grid connectivity has a positive effect (Njeru et al., 2020). These findings suggest that optimizing O&M practices, along with implementing market reforms and encouraging competition, can enhance firm performance in the electricity sector (Hou et al., 2024).

Research on the impact of firm age on performance presents mixed findings across different sectors and contexts. Sattar et al. (2013) found that firm age significantly affects performance, with older firms tending to perform worse due to higher levels of short-term debt. Similarly, Ismail and Jenatabadi (2014) observed that firm age moderates the relationship between internal operations, economic conditions, and overall performance in the airline industry. In contrast, Megawati (2019), in a study of 162 manufacturing firms using purposive sampling, found that firm size and leverage significantly influenced performance, while firm age and growth did not. This finding aligns with Ekadjaja and Wijaya (2021), who also reported that firm age does not significantly impact firm performance. However, in the energy sector, Njeru et al. (2020) reported an average technical efficiency of 71% in Kenyan thermal power plants and identified plant age as a key contributor to inefficiencies. These contrasting results suggest that the influence of firm or plant age on performance may vary across industries and may depend on factors such as debt structure, sector-specific dynamics, and operational practices.

Technological and organizational innovations are widely acknowledged as key drivers of energy efficiency across sectors, particularly in electricity generation. Huang et al. (2022) demonstrated that adopting robots in production processes can significantly improve firms' energy efficiency by streamlining operations and minimizing energy waste. In addition to internal technological upgrades, the type of energy source used in electricity generation plays a crucial role in determining firm-level efficiency. Saglam (2018) found substantial variation in the efficiency of different renewable energy technologies, with geothermal energy being the most efficient and solar thermal the least. Expanding on this, Mekuye et al. (2024) noted that renewable energy sources are generally more efficient and sustainable than their nonrenewable counterparts, which contributes to improved overall performance of electricity-generating firms. These insights suggest that both the adoption of advanced technologies and a strategic shift toward more efficient renewable energy sources are essential for enhancing firm efficiency in the electricity sector.

The relationship between firm size and efficiency in energy generation and manufacturing is complex and varies across different contexts. While some studies, such as Shumais (2020), find no significant relationship between firm size and efficiency, others report that larger plants tend to be more efficient (Kusz et al., 2024). Specifically, in Austrian biogas plants, smaller facilities (under 100 kW) showed scale inefficiencies, with increasing returns to scale being observed as plant size grew (Eder & Mahlberg, 2018). However, Kusz et al. (2024) found that small biogas plants in Poland achieved similar technical efficiency levels as larger ones, suggesting that smaller plants can still be efficient under certain conditions. Beyond firm size, other factors also play a crucial role in determining efficiency. Ownership structures, the adoption of solar PV technologies, the regulatory environment (Bernstein, 2020), and subsidies (Eder & Mahlberg, 2018) have been identified as key influences, with subsidies showing a negative relationship with managerial efficiency. In the manufacturing sector, firm size has been found to reduce technical inefficiencies in the electrical and electronic industries (Megawati, 2019), and Costa-Campi et al. (2015) highlighted that firm size is a significant determinant of energy efficiency improvements in Spanish manufacturing firms. These findings emphasize that while firm size can influence efficiency, its effect is also moderated by other operational and external factors.

3.0 Methodology

3.1 Research design:

The study used a quantitative research design to compare the technical efficiencies of the generators and identifying the factors influencing the technical efficiency in energy generation. This design is suitable because it facilitates the rigorous, objective measurement of technical efficiency across multiple generators using DEA, offering a clear, data-driven perspective on performance of the DMUs.

3.2 Population study

The study focused on 50 electricity generating companies in Uganda (MoEMD, 2023). This included all the companies or entities involved in the generation of electricity, such as public companies, private companies, and any other public or private power plants operating in the country.

3.3 Data Source and processing

This study use a time series data (secondary data) from Uganda's Electricity Regulatory Authority's (ERA's) website (https://www.era.go.ug/index.php/stats), covering the period from 2016Q1 to 2023Q4, selecting the generation statistics. This was based on the availability of the data or observations.

After obtaining the data from ERA, to ensure that the data is complete and accurate, cleaning (to cater for missing values and correcting anomalies), transforming the variables, and categorizing or aggregating data, were done. After thorough data cleaning, 36 electricity generating firms (utilities) were maintained for further analysis using STATA software Version 15.

3.4 Data analysis

The purpose of this study is to examine the technical efficiency among the electricity generating firms in Uganda and categorize factors that affect technical efficiency. Based on the Efficiency Measurement and Scale Efficiency Theories, the conceptual model integrates both technical and scale efficiency.

The study therefore employed a mathematical model of Data Envelopment Analysis (DEA), a non-parametric technique, particularly an Input-Orientation DEA model (Toloo et al., 2020; Tharwat et al., 2019; Ji & Lee, 2010). This model is used to test if a DMU can reduce (minimize) the inputs while keeping outputs constant (Piran et al., 2020; Khan & Karam, 2019).

DEA models can also be subdivided in terms of returns to scale. Charnes et al. (1978) originally proposed the efficiency measurement of the DMUs for constant returns to scale (CRS), where all DMUs are operating at their optimal scale. Later Banker et al. (1984) introduced the variable returns to scale (VRS) efficiency measurement model, allowing the breakdown of efficiency into technical and scale efficiencies in DEA.

At the second stage, using a Tobit regression Model, the values of Technical Efficiency (TE) derived were regressed on the input variables (regressors) to identify the factors influencing technical efficiency of generating firms. Therefore, the second stage model had the following form;

$$TE_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \dots \dots \dots \dots \dots \dots + \beta_n x_n + \varepsilon_i \qquad (5)$$

Where

$$TE = Technical\ efficiency\ values$$
$$\beta_i = coefficiencts\ of\ the\ varaibles, i = 1, 2, 3, \dots \dots n$$
$$\beta_0 = constant\ (Average\ technical\ value)$$
$$x_i = independent\ viriables\ of\ interest$$
$$\varepsilon_i = the\ error\ temr$$

Therefore the model specification is;

$$TE = \beta_0 + \beta_1 number\ of\ employees + \beta_2 O\&M\ costs + \beta_3 Plant\ size + \beta_4 Energy\ source + \beta_5 Firma\ age + \varepsilon \qquad (6)$$

Where;

$$TE = technical\ efficiency\ of\ firm\ i\ in\ year\ t,$$
$$\beta_i = are\ variable\ parametors$$
$$\varepsilon = the\ error\ temr$$

The Tobit regression model is a vital tool in econometrics and various other fields for analyzing censored data (Karim & Salh, 2020). It provides a framework to understand both the occurrence and magnitude of outcomes when the dependent variable is subject to censoring. By appropriately modeling the data-generating process, the Tobit model yields unbiased and consistent parameter estimates, offering deeper insights into the factors influencing the censored dependent variable (Michels & Musshoff, 2022; Sedeeq & Meran, 2022; Jacobson & Zou, 2024).

3.5 Variable under the study and integration into the model

Table 1: Variables under study and the data source

Variable	Symbol	Variable definition/ interpretation	Source of Data	Measurement units
Technical Efficiency	TE	Technical efficiency score of a generating firm (DMU)	Author's compilation	Percentage
Total Revenue	TR	Total revenues generated in a year	ERA (Website)	UGX Million

Number of employees	NE	Number of employees of each generating firm (DMU) at the end of a year	ERA (Website)	Number
Operation & Maintenance cost	O&M	Total operational and maintenance costs (Salary, repair, raw materials, fuel etc.)	ERA (Website)	UGX. Million.
Power plant size	Psize	Installed capacity of power plant	ERA (Website)	MWh
Energy generated	TEG	Total energy generated by a firm	ERA (Website)	MWh
Energy source	Source	Type of energy source	ERA (Website)	N/A
Age	Age	Years since the power plant started electricity generation	ERA (Website)	Years

In this study, Total revenues (TR) was used as the output variable, while Energy generated (TEG) as energy generated, number of employees (NE), Operation and Maintenance Costs (O&M), Plant size (Psize) as the installed capacity of the plant, Energy source (Source), and Age (Years of existence in electricity generation), were considered in this study. Some of these variables were used to calculate the technical efficiency of each DMU and also to establish factors influencing the technical efficiency in the DMUs.

4.0 Results

4.1 Descriptive statistics

From Table 2, the average energy generated in the period of study is 838,137MWh, average number of employees is 517 people per year, while average Operation & maintenance costs is UGX: 522,761.8 Million shillings.

Table 2: Descriptive statistics of the variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total Energy Generated	36	838,137	2,384,326	18502.45	10,100,000
Number of Employees	36	516.5	566.9875	56	3323
Operation & Maintenance	36	522,761.80	2,232,713	804	12,500,000

Source: Author's computation

4.2. Multicollinearity test

Table 3. Results of Multicollinearity test

Variable	VIF	1/VIF
Total Revenue	1.31	0.72451

Energy generated	1.4	0.65432
Number of Employees	1.3	0.76724
Operation & maintenance costs	1.3	0.767247
Mean VIF	1.31	

Source: Author's computation

From the table, since the mean VIF =1.3 is less than 10 (threshold) (Gujarati, 2004), the results show that there is no severe multicollinearity in the variables considered.

4.3 Data Envelopment Analysis results

Using DEA, the study conducted a benchmarking approach to determine performance (technical efficiency) of the utilities in a specified period. 36 generating companies or utilities were considered as the Decision-Making Units (DMUs). This means that the sample had 36 data values which is greater than 30 sample size, enough for analysis. DEA analysis enables the efficiency of each DMU to be calculated in order to make comparisons between the units of the group analyzed, highlighting the best. According to Koopmans (1951), a firm will be considered efficient if there is any improvement in the input or output without affecting or harming (worsening) some other input or output. Also, with a study by Alirezaee and Afsharian (2010) an efficient DMU in CRS model is also considered efficient in the VRS model.

Technical Efficiency score were generated using DEA Model in STATA software, for each DMU. For this study, VRS model (Banker et al., 1984) was applied as the best technique to achieve the purpose of the study. See table 4 for results. The scores in the table were sorted depending on the ranks, considering those with high scores first (100%) to those less than 100% efficiency score.

4.3.1 Technical Efficiency Score by firms

From Table 4: Data Envelopment Analysis (DEA) results by generators

No	Generators	rank	Efficiency Scores (theta)	islack (NoE)	islack (O&M)	islack (TEG)	islack (TR)
1	Bujagali	1	1	.	0	.	.
2	Emerging Solar Power	1	1	.	.	0	.
3	Isimba	1	1	.	0	.	.
4	Kabalega Hydromax	1	1	.	.	.	.

5	Kiira & Nalubaale	1	1	0	.	.	0
6	NKUSI (PA Technical)	1	1	.	.	.	.
7	Nyamwamba 2	8	1	.	.	482508	85891.8
8	SM Hydro	1	1	.	.	.	0
9	ACCESS Solar	9	0.872205	.	.	8445.4	.
10	UEGCL Namanve (Jacobsen)	10	0.859978	.	.	794843	.
11	Tororo Solar (North)	11	0.73972	.	.	205531	19032.9
12	Kakaka	12	0.502665	.	.	211697	34980.4
13	Tororo PV Power	13	0.410587	.	.	252063	33403.7
14	Hydromax Nkusi (Waki)	14	0.384575	.	.	.	0.000103
15	TIMEX Bukinda	15	0.383014	.	.	22029.5	.
16	ZIBA	16	0.371187	.	.	.	.
17	XSABO Solar	17	0.351845	.	.	20670.3	.
18	Nyamagasani 2	18	0.336801	.	.	124281	22614
19	Kilembe Mines Ltd (KML)	19	0.333675	.	.	.	20270.2
20	SINDILA	20	0.32907	.	.	45506.1	8454.77
21	Ndugutu	21	0.309966	.	.	21288.7	2151.64
22	Rwenzori Hydro	22	0.295498	.	.	106949	11399.5
23	SITI 2	23	0.294499	.	.	184139	10856
24	Muvumbe Hydro (U) Ltd	24	0.282221	.	.	3320.49	.
25	Kikagati	25	0.263281	.	320.99	482241	156213
26	Achwa 1&2	26	0.26278	.	.	1924397	61033.9
27	Elgon Hydro SITI	27	0.248041	.	.	5963.84	.
28	Electromaxx (U) Ltd	28	0.233961	.	.	628906	.
29	Lubilia	29	0.224496	.	.	5883.99	.
30	Maji-Power Bugoye Ltd	30	0.219021	.	.	496033	38046.6
31	Kasese Cobolt Company Ltd	31	0.214418	.	.	.	.
32	Mahoma	32	0.194277	.	.	893.937	0.001457
33	Rwimi	33	0.165583	.	.	450381	39808.5
34	Ecopower - Ishasha	34	0.135528	.	.	85356.8	5863.01
35	AEMS-Mpanga	35	0.13504	.	.	482568	22481.6
36	Nyamwamba	36	0.10913	.	.	473205	135760

Source: Author's computation

From the results in Table 4 reveal that only 22% of the total electricity generating firms achieved 100% technical efficiency during the study period (2016-2023). However, a significant portion, 66.6% of the electricity generating firms operate at less than 50% technical efficiency, with 41.7% of these performing below 30% technical efficiency. 77.8% the electricity generating firms considered have their efficiency scores range from 10% to 87%, indicating substantial inefficiencies in power generation across sector.

Most electricity generating plants in Uganda show no slack in the number of employees or operation and maintenance costs (O&M), indicating efficient use of labor and maintenance resources. However, Kikagati exhibits a notable slack of 320.995 in O&M costs, suggesting it spends more on maintenance than necessary for efficient operation.

Slack values in total energy generated reveal inefficiencies in production. Generating plants under-produce relative to their input use. Additionally, positive slack values in total revenues, indicate under-performance in revenue collections with current resource levels. These inefficiencies pose challenges for the electricity sector and broader economic growth, as underperforming plants contribute sub-optimally to the energy supply. Nevertheless, the absence of slack in workforce deployment suggests higher labor efficiency. Overall, the findings highlights significant potential for improving energy generation and revenue efficiency across Uganda's electricity sector.

4.3.2 Technical Efficiency Score by Firm Age

From Table 5: Data Envelopment Analysis (DEA) results by years of existence

DMU	rank	Efficiency Scores (theta)	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
More than 10 Years of existence						
Kiira& Nalubaale	1	1	0	.	0	.
Kasese cobolt	6	1	.	.	40234	1032561
Kilembe Mines Ltd	4	1	.	.	114710	253809
UEGCL Namanve	5	1	.	.	68489.2	1002357
Electromaxx (U) Ltd	10	0.503243	.	.	376389	1765226
Maji-Power Bugoye	8	1	.	.	934988	2796444
AEMS-Mpanga	9	0.580402	.	.	872040	2460420
Bujagali	1	1	.	0	.	.
Ecopower-Ishasha	7	1	.	.	. 40390	1205673
Kabalega Hydromax	1	1	.	.	.	
Between 6 to 10 years of existence						
DMU	rank	theta	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
Access Solar	4	0.872971	0.878974	.	.	8452.95
Elgon Hydro Siti	15	0.255685	31.7575	.	.	6229.47
Muvumbe Hydro (U) Ltd	14	0.294286	67.2663	.	.	3886.69
Rwimi	18	0.201675	.	.	61056.5	584857
Tororo PV power	7	0.457831	.	.	40198.4	288865

Tororo Solar (North)	5	0.803212	.	.	24147.4	232008
Hydromax Nkusi (Waki)	6	0.468206	270.579	.	3112.91	.
Isimba	1	1	.	0	.	.
Lubilia	17	0.23028	22.9882	.	.	6075.65
Mahoma	16	0.234984	18.9336	.	8329.77	21470.1
Nkusi (PA Technical)	1	1	.	.	.	0
Nyamwamba	19	0.137443	.	4707.81	72517.9	644913
Xsabo Solar	9	0.355957	15.4635	.	.	20803.6
Achwa 1&2	11	0.329057	.	5273.19	39965.8	2443198
Emerging Solar Power	1	1	.	.	.	0
Ndugutu	13	0.311675	.	.	2342.86	21852.7
Sindila	10	0.334802	.	.	9077.73	47480.9
SITI 2	12	0.322803	.	.	16467.7	212073
Ziba	8	0.411841	159.07	.	.	0.009758
Between 1 to 5 years of existence						
DMU	rank	theta	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
Timax Bukinda	1	1	.	.	.	.
Kakaka	5	0.720178	.	.	0.000604	2646.03
Nyamagasani 2	7	0.557648	.	.	0.00049	3602.88
Nyamwamba 2	1	1	.	.	0	.
Rwenzori Hydro	6	0.692551	.	.	.	4046.47
Kikagati	1	1	.	0	.	.
SM Hydro	1	1	.	.	.	.

Source: Author's computation

Table 5 highlights varying technical efficiency levels among electricity generating firms in Uganda based on their operational age. Firms older than 10 years show high average efficiency (90%) but still face inefficiencies in energy generation and revenue. Mid-age firms (6-10 years) perform the worst, averaging 47.5% efficiency, with several showing significant slacks. Newer firms (1-5 years) demonstrate better performance (85.3% average), likely due to modern technologies and streamlined operations, though minor inefficiencies remain. Overall, while older and newer firms tend to be more efficient, operational improvements are needed across all age groups to address persistent output and revenue inefficiencies.

4.3.3 Technical Efficiency by Energy Source

From Table 6: Data Envelopment Analysis (DEA) results by Energy source

Firms	rank	Efficiency Scores (theta)	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
HYDRO POWER PLANTS						
Kiira & Nalubale	1	1	0	.	0	.
Kasese Cobolt Company Ltd	23	0.223963	.	.	.	0.023432
Kilembe minES Ltd (KML)	16	0.333675	.	.	20270.2	.
Maji-Power Bugoye	24	0.223068	.	.	41738.3	514608
AEMS-Mpanga	28	0.137962	.	.	26407.1	506996
Bujagali	1	1	.	0	.	.
ECOPOWER-Ishasha	27	0.150769	.	.	.	126639
Kabalega HydromaxX	1	1	.	.	.	.
Elgon Hydro SITI	19	0.278857	.	.	.	16535.2
Muvumbe Hydro (U) Ltd	18	0.296266	.	.	.	9790.3
RWIMI	26	0.172423	.	.	42136.9	478239
Hydromax Nkusi (WAKI)	11	0.389922	.	.	.	.
Isimba	1	1	.	0	.	.
Lubilia	21	0.259901	.	.	.	17499.4
Mahoma	22	0.228896	.	.	.	9660.43
Nkusi (PA Technical)	1	1	.	.	.	.
Nyamwamba	29	0.10913	.	.	135760	473205
Achwa 1&2	25	0.212023	.	.	.	1406978
Ndugutu	13	0.365141	.	.	.	39835.9
Sindila	12	0.372069	.	.	.	76603
SITI 2	17	0.327757	.	.	6900.16	231697
Ziba	10	0.398622	.	.	.	.
TIMEX Bukinda	9	0.447933	.	.	.	45340.8
Kakaka	8	0.530173	.	.	28916.1	238010
Nyamagasani 2	14	0.364199	.	.	14361.3	154940
Nyamwamba 2	7	1	.	.	85891.8	482508
Rwenzori Hydro	15	0.334243	.	.	5122.88	149862
Kikagati	20	0.263281	.	320.995	156213	482241
SM Hydro	1	1	.	.	.	0
SOLAR POWER PLANTS						
Firms	rank	theta	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
ACCESS Solar	1	1	.	0	.	.
Tororo PV Power	5	0.457831	.	2605.85	9503.42	22138.8
Tororo Solar (North)	4	0.893033	.	2524.95	1163.21	3772.15
XSABO Solar	1	1	.	0	0	0
EMERGING Solar Power	1	1	.	.	.	.
THERMAL POWER PLANTS						

Firms	rank	Efficiency Scores (theta)	islack (NoE)	islack (O&M)	islack (TR)	islack (TEG)
UEGCL Namanve (JACOBSEN)	1	1	.	0	.	.
ELECTROMAXX (U) Ltd	2	0.720155	0.0002	31276.6	100306	133901

Source: Author's computation

The results show notable differences in technical efficiency among electricity generating firms based on their energy source Hydro, Solar, and Thermal. Hydropower plants exhibit a wide efficiency range, with some operating efficiently while others show low scores (13.7% - 22.3%) and high slack values in energy generation, indicating underutilization of capacity.

In contrast, solar plants generally perform better. Access solar, XSABO solar, and Emerging Solar power operate at full efficiency, while Tororo PV Power (45.7%) Tororo Solar (North) (89.3%) show moderate inefficiencies, mainly in revenue and energy output. However, their slack values are relatively low, suggesting fewer issues in resources utilization compared to hydropower firms. Generally, Hydro power plants show more inefficiencies than solar power or thermal plants, suggesting that further optimization and resource management improvements are necessary, especially for the hydroelectric sector.

4.4 Analysis of the factors influencing Technical Efficiency using Tobit regression model

Table 7 shows the analysis results by a Tobit regression model of factors influencing technical efficiency in electricity generation in Uganda. Both CRS and VRS models were applied. However, in this study, the VRS model results were considered important and appropriate method to achieve the purpose of the study.

Table 7. Tobit results under both CRS and VRS model

Tobit regression - CRS Model				**Tobit regression - VRS Model**			
Number of Observation			36	Number of Observation			36
Uncensored			32	Uncensored			28
Left censored			0	Left censored			0
Right censored			4	Right censored			8
LR Chi2(5) =			32.11	LR Chi2(5) =			36.41
Prob value>chi2=			0.000	Prob value>chi2=			0.000
Pseudo R2 =			0.59397	Pseudo R2 =			0.7762
CRS_TE	**Coef.**	**t-values**	**P-values**	**VRS_TE**	**Coef.**	**t-values**	**P-values**

Plant Size	0.31534	6.21	0.000	Plant Size	0.41187	6.3	0.000
Number of Employees	-0.05403	-0.77	0.448	Number of Employees	-0.19808	-2.52	0.017
O&M costs	-0.22257	-4.99	0.000	O&M costs	-0.24001	-4.75	0.000
Firm Age	0.21829	2	0.054	Firm Age	0.18192	1.5	0.143
Energy source				Energy Source			
Solar	-0.10529	-0.73	0.468	Solar	-0.3245	-2.03	0.051
Thermal	-0.21802	1.24	0.224	Thermal	-0.33381	-1.7	0.635
Constant	1.73138	4.65	0.000	Constant	2.85172	6.54	0.000

Source: Author's computation

The censored regression model under the CRS DEA framework shows that plant size positively and significantly boosts efficiency (Coef. = 0.31534, p-value = 0.000), while firm age shows a marginal positive effect (Coef. = 0.21829, p-value = 0.054). Conversely, high O&M costs significantly reduces efficiency (Coef. = -0.22257, p-value = 0.000), whereas workforce (number of employees) and energy source have a negative but statistically insignificant impacts.

The Tobit regression results under VRS DEA Model highlight key factors influencing technical efficiency (VRS_TE). Plant size positively and significantly effects technical efficiency (Coef. = 0.41187, P-value=0.000), suggesting that larger plants perform better under VRS conditions. In contrast, number of employees negatively effects technical efficiency (Coef. =-0.19808, p-value = 0.017), suggesting potential inefficiencies from overstaffing. Similarly, high O&M costs significantly reduces efficiency (Coef. = -0.24001, P-value =0.000). This enforces the need for cost-effective management practice. Energy source also has a negative and statistically significant impact, with solar energy (Coef. = -0.3245, p-value 0.051), showing a lower likelihood of inefficiency compared to hydro energy. This study consider the results by VRS model as the appropriate results for policy implication.

5.0 Discussion, Conclusion and Recommendations

5.1 Discussion of the Results

The technical efficiency results indicate that 22% of the electricity-generating firms operate at full capacity, while significant 77.85 exhibited efficiency scores ranging from 10%-87%. Notably, 67% of them operate below 50% efficiency, with 41.7% falling below 30%. These findings highlight significant inefficiencies within the sector, potentially due to suboptimal input utilization, outdated technology and regulators constraints.

Studies, such as Ajayi et al. (2020), indicate that regulation and energy policies can negatively impact energy sector productivity, often due to inefficient resource use and outdated technology. However, targeted measures like regulatory reforms, modern infrastructure investments, and capacity building can enhance efficiency. Rahimi and Ipakchi (2010) emphasize demand-side management and technological innovation as key to optimizing electricity generation. Likewise, Bigerna et al. (2016) highlight the effectiveness of incentive-based regulations, particularly in emerging economies where state-owned utilities often struggle with efficiency.

Firm age significantly influences efficiency, with older firms (>10 years) exhibiting relatively high average efficiency (90%) but some inefficiencies in output. Firms aged 6–10 years struggle with workforce inefficiencies and revenue constraints, with 74% operating below 50% efficiency. These results are consistent with Alam and Arshad (2020), who found that firm maturity often leads to better efficiency due to experience and economies of scale. Conversely, the study contradicts findings by Chen et al. (2019), who suggest that younger firms often exhibit higher efficiencies due to their adoption of modern technologies and lean operational structures. The performance of firms in the 1–5-year range, with efficiency above 55%, supports this alternative argument.

The Tobit regression results highlight that plant size positively affects efficiency, whereas workforce size, O&M costs, and energy source negatively impact efficiency. These findings align with the work of Rickels et al., (2020), who noted that hydro plants in developing economies face operational and maintenance challenges that lower their efficiency. Meanwhile, the higher efficiency of solar and thermal power plants is supported by studies like Owusu and Asumadu-Sarkodie (2016), who attribute this to lower maintenance costs and higher capacity utilization. These results suggest a need for improved operational strategies to enhance efficiency in the electricity sector.

The VRS model results suggest that improving technical efficiency in electricity generation requires strategic interventions in plant size, workforce management, cost control, and energy technology. The positive impact of plant size indicates that scaling up generation plants or enhancing operational capacity can improve efficiency, while the negative effect of workforce size suggests the need for labor optimization through better management, automation, and training. The significant influence of O&M costs highlights the importance of adopting cost-effective maintenance strategies, such as predictive maintenance and automation, to reduce inefficiencies. Additionally, the negative effect of solar energy on efficiency underscores the need for investment in advanced storage solutions, hybrid systems, and grid integration technologies to enhance renewable energy performance. Policymakers should focus on creating regulatory frameworks and incentives that promote efficiency, including tax breaks for firms adopting best practices in cost and labor management, as well as increased investment in research and development to improve energy generation efficiency.

5.2 Conclusion

Uganda’s electricity generation sector faces inefficiencies, with 77.8% of the generating firms operating below optimal efficiency, largely due to outdated technology, regulatory constraints, and high operational costs. Hydropower plants, the dominant energy source, are less efficient than solar and thermal plants, highlighting the need for improved maintenance strategies and diversification of energy sources. Larger power plants tend to be more efficient, while high workforce size and O&M costs negatively impact performance. Furthermore, older firms perform better, while mid-age-firms struggle, indicating the need for targeted support and efficiency-enhancing policies. Addressing Uganda’s electricity generation and overall economic growth.

5.3 Recommendations

Policymakers should implement efficiency-driven regulations, providing incentives for firms adopting modern technology while enforcing accountability for underperforming ones. Performance-based regulations, tax breaks, and efficiency audits should be introduced to ensure firms operate optimally. Additionally, policies should support diversification of Uganda’s energy mix, encouraging hybrid systems like solar-hydro integration to improve overall efficiency.

Electricity generating companies must enhance operational efficiency by adopting predictive maintenance strategies, digital monitoring, and automation to minimize downtime and operational costs. Hydropower plants, which exhibit the most inefficiencies, should focus on resource optimization and benchmarking against efficient firms. Workforce management should also be optimized through better training programs, lean staffing, and process automation to improve productivity.

Investors and financial institutions should prioritize funding for firms demonstrating strong efficiency metrics, adopting a performance-based lending model. Special financial support programs should be introduced for mid-age firms (6–10 years) that struggle with efficiency, enabling them to scale up operations and invest in cost-saving technology. Investments in smart-grid technology and energy storage systems should also be encouraged to enhance electricity generation and distribution efficiency.

Uganda's energy sector must focus on cost-effective maintenance strategies and improving labor productivity to address inefficiencies. Capacity-building programs and technical support should be provided to underperforming firms to help them transition into high-efficiency operations. A combination of regulatory reforms, investment incentives, and technological advancements will be key to improving electricity generation efficiency and ensuring sustainable energy growth.

5.4 Future areas for Research

- Future studies should look at exploring panel or longitudinal data for long time period to analyze how efficiencies involve overtime.
- Also, other authors should explore employing alternative statistical or econometric models could provide deeper and detailed insights about efficiencies in energy sector, specifically in electricity generation in Uganda.

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