# Towards an efficient tariff system in the electricity distribution: Evidence from Uganda

ABSTRACT

This study investigates incentive regulation to foster an efficient tariff system in the electricity distribution subsector in Uganda. This study seeks to find empirical evidence to support the argument that regulation is associated with efficiency among distributors. It seeks to design an appropriate model of incentive regulation within the distribution subsector. It assesses the efficiency of existing tariff setting system with a view of guiding policy on how best incentives should be appropriated.

It uses the data envelopment analysis and stochastic frontier analysis to investigate how distribution firms use input costs to come up with an efficient end user tariffs. Quarterly data used is from Electricity Regulatory Authority (ERA) covering the period 2013-2019.

The findings are that distribution firms cost inputs are inconsistent with the way they their operational and maintenance costs are generated and transmitted to end user tariff. The regulator should be keen on the way tariff is set such that it is fair to all players in the electricity markets.

Incentive regulation has a positive influence on cost efficiency and end user tariff. A reduction in energy losses and energy purchases from transmitter makes up the most efficient cost drivers. Lastly, tariff regulation has increased efficiency in operations through in improved quality and reliability of power distribution. First and foremost is reduced load shedding, secondly is more reliable power distribution to end users. Appropriate Incentive regulation has a direct effect on cost of utility and in increasing access of vulnerable groups.

*Keywords:* Incentive regulation, efficient tariff, Data Envelopment Analysis, Stochastic frontier Analysis, Uganda



## 1. Introduction

Electricity distribution firms enjoy a preserve of natural local monopoly, this creates a need for sound regulatory regime to deliver efficiency gains to all stakeholders [1]. This monopoly would breed inefficiency hence the need for market regulation [2].

A study of electricity regulation operates a production frontier with stochastic features that ought to be integrated on a deterministic parametric frontier [3]. This would reveal the level of efficiency at which firms operate.

World over, long term regulatory contracts enhance investments into the electricity infrastructure. Physical infrastructure in the sector is mainly fixed costs. Short term regulatory regimes are able to influence operational costs. The regulator extracts the firm’s rent, the firm will have no additional financial resources to invest and achieve overall efficiency [4].

Inadequate regulatory credibility leads to gross underinvestment [5] [6]. After undertaking market reforms, incentive regulation may be adopted. In Uganda, Electricity Regulatory Authority (ERA) preferred to adopt a price cap where constraints are placed on the path of price increases which are capped not exceeding 6% per quarter for power supplied by distributors to end-users. This therefore raises a key question on the optimal regulatory mix that would achieve efficiency gains.

With regulates prices, UMEME another distribution company in Uganda can increase profits by reducing costs or increasing sales. This means that unexpected cost changes are borne by the firm. This is effective in supply-side management [7]. Price cap, however, can deter investment and reduce service quality this is the case with UMEME Ltd expanding grid infrastructure and increasing power reliability.

Most effort in promoting efficiency in the developing world is by minimising cost. However, this can easily lead to service deterioration (Benerjee 2003). It may increase social welfare due to efficiency gains in a lower tariff, this has not been the case with Uganda where the electricity supply capacity is 1352MW and at a tariff of US $ 0.2, peak demand is 850MW, leaving a reserve capacity of 40 % (ERA, 2022).

Revenue cap regulation, where constraints are placed on regulated firm’s revenues, this provides more incentives to demand side management (Jarvis, 2011). This scheme encourages cost reduction and energy saving through flexible price adjustments. Under a binding revenue cap Firms can increase profits by reducing costs either through reductions in output or increasing price. This tariff is reflective of utility’s costs and with inelastic demand, an increase in price will reduce quantity of electricity demanded; total cost will also reduce by a greater proportion hence leading to increased revenue. This was proposed by Jamison (2007), supported by Lantz (2008) who suggested that revenue cap should be used when the firm’s cost function is available to the regulator.

Revenue cap has substantial reductions to social welfare since it deviates from the Ramsey pricing rule. In all an optimal incentive scheme should be designed to address the principal agent problem associated with asymmetric information Laffont and Tirole (1993), the principal regulator has far less information about regulated firm’s operation (agent). For instance the regulated firm has more information about the cost of providing electricity and consumer demand behaviour than ERA.

There exist complex contractual relations requiring substantial information between ERA and UMEME. Kopsakangas- Savolainen and Svento (2010) show that the menu of contract regulation provides sufficient incentives to solve the moral hazard and adverse selection problem. The hypothesis is that regulation should reinforce efficiency in tariff setting.

This study hypothesizes that regulation is associated with efficiency among distributors [8]. It will also design an appropriate model of incentive regulation within the distribution subsector. It will also assess the efficiency of existing tariff setting system with a view of guiding policy on how best incentives should be appropriated.

Most studies on efficient have focused on revenue and price cap, this study further, interrogates the regulator's role in promoting efficiency in the distribution subsector

The rest of the paper is structured in the following way; section two is overview of the Electricity Regulatory system in Uganda, while section three is literature review while section four is methods, section five is findings and discussion, and finally is conclusion and policy recommendations.

## 2.0 Review of the Electricity Regulatory system in Uganda

The electricity regulation under liberalized incentive regulation is about two decades as explained below.

### 2.1 Electricity Regulatory Authority (ERA)

ERA was formed in 2000 following the unbundling of Uganda Electricity Board (UEB) in November, 1999. It provided the legal structure as enshrined in The Electricity Act (Act 6, 1999) CAP 145 Laws of Uganda 2000 edition. Its core functions included issuing licenses for generation, transmission, distribution of electricity; establishing a tariff structure and investigating charges, whether or not a specific complaint has been made for a tariff adjustment; approving the rates of charges, terms and conditions of electricity services provided by transmission and distribution companies and to develop and enforce performance standards for the generation, transmission and distribution of electricity. The development of electricity subsector would foster economic growth [9],[16].

The tariff structure was spelled out in the section 75 of the Act referred to as the Electricity (Tariff Code) Regulations, 2003. The code provides for tariff objectives; principles of tariff setting, ERA is guided by two main considerations; Whether the revenue requirements as applied for by operators are fair and reasonable in light of the objective of continuity of supply and affordability; and whether the proposed tariff regimes balance the interest of all the stakeholders, which include, current and potential consumers, government, and licensees.

Tariff setting is guided by the following objectives: To provide consumers with fair and reasonable price structures consistent with maintenance of a financially and operationally secure electricity supply system; Encourage consumers to make efficient use of energy based on price signal; encourage operators to make efficient use of plant (assets) and operational efficiency based on financial benefits and penalties; provide operating companies reasonable return/profit to give confidence to current investors and attract new investors; Provide a tariff structure for cost reflective tariff for each customer group; and Provide for future progress towards a commercially competitive system.

Benchmarking of efficiency gains by the regulator is associated with four objectives include; Providing a fair and reasonable rate of return on efficient investment- given efficient operating and maintenance practices, foster existing use of resources and existing network, encourage efficient behaviour by service providers and incentives to increase productivity, and provide an equitable allocation of efficiency gains.

The tariff structure is set at three points in the industry: At the interface between generation and transmission; at the interface between transmission and distribution; and at the interface between distribution and end-user consumers. The elements of end user tariffs are; fixed standing charges; capacity (demand) charges; and energy or usage charge

### 2.2 The electricity distribution subsector

#### 2.2.1 Introduction of the Electricity subsector in Uganda

There are eight distribution companies in the country. These include UMEME Ltd, Uganda electricity distribution Company (UEDCL), West Nile Rural Electrification Company (WENRECo), Bundibugyo Energy Electric cooperatives (BECs), Pader and Abim Multipurpose Electric Cooperatives (PACMECs), Kilembe investment limited (KIL), Kalangala Infrastructural Services (KIS) and Kyenjojo Rural Electric cooperatives (KRECS). We focus on UMEME distribution network because it is the largest distributor.

#### 2.2.2 UMEME distribution network

UMEME operates under a concession with a structural monopoly on the distribution of electricity across Uganda, distributing 95% of electricity in Uganda through a single buyer model. As of 2019, the UMEME distribution network was a total of 57,133 Kilometres consisting of 27,037 kilometres of 33KV lines, and 29,096 km of low voltage below 11KV lines. It has 77 substations and over 10000 pole-mounted transformers, low-voltage (less than 1 kV) distribution wiring and meters. The control centre at Lugogo controls 35 out of the 77 substations. It only controls up to the substation level not the feeders. For communication to the control centre, the substations and control centre are connected by a combination of fibre optic and GPRS links. The fibre optic links are used in urban areas, the GPRS links are used for the substations that are far away from Lugogo.

## 3. Empirical literature

[10] pioneered work of market based reforms in Britain, privatisation and competition in the energy industry, their findings are that appropriate unbundling fosters rationalisation of the energy sector with better quality of service, while [7] had relayed useful information regarding the source of cost information and cost reduction potential and whether use a single regulatory contract or benchmarks to achieve a comprehensive incentive scheme.

Campbell (2018) evaluated the behaviour of electricity providers under conditions of asymmetric information, with more elastic demand revenue cap prices are larger than price cap regulation. Revenue cap promotes energy conservation and reduces social welfare. He concludes that price cap regulation is more appropriate in developing countries with considerable inflation tendencies while global oil markets also favourprice revenue cap with more electricity supply constraints and climate change. [11] examined tariff model considering the technological, environmental and structural changes which bring electricity markets closer to a complex system. Electricity tariffs are based on a tight separation of electricity demand and supply, with a regulatory policy controlling for electricity supply given aggregate demand structure.

According to [11] the complex adaptability system has a lot of interdependence hence giving rise to the principal agent problem. [4] used GMM to analyse Russia's tariff reform structure and found that both revenue and price cap promoted sufficient investments into the electricity infrastructure under long term regulatory regimes.

## 4.0 Methods

### 4.1 Data source

Quantitative data will be used from ERA and supplemented by data from various distributors to enable corroboration of findings and enhancing data validity (Kamukama 2010, Ntayi, 2005, Gherardi & Turner 1987). It will be Panel data sets that will be used. This study uses a balanced panel data set consisting of six electricity distributors for a period of 6 years 2013–2019.Choosing and measuring variables for efficiency analysis takes into account the diversity and compound services that distributors offer. The regulator's key objective is promoting cost efficiency, we use knowledge on each utility's main demand and cost drivers to choose inputs, outputs, and environmental variables (Coelli et al., 2003).

For purposes of making benchmarks on the selected parametric and non-parametric methods and guiding decision making. 2 distribution companies, Kalangala Infrastructure Services (KIS) and West Nile Rural Electrification Company (WENRECO) were excluded for absence of data. These are small distribution companies with their own mini grids. A panel consisted of 28 series and 168 observations which are adequate for purposes of assessing technical efficiency.

### 4.2 The econometric models expounded

Efficiency studies use both parametric and non-parametric measures, the choice of a specific model over another remains hotly contested [12] (Seiford& Thrall 1990, Berger 1993). This study uses both approaches as appropriate to derive results on efficient incentives regulation. The econometric models of interest to this study seek to explain efficiency in the distribution regulation system.

#### 4.2.1 The Data Envelopment Analysis (DEA) Model

DEA is a non-parametric technique of benchmarking the most effective activity by using linear programming to examine the nature of costs and provide relative efficiencies of decision making units (DMUs) Jamasb (2003). It shows the most productive combination on the production frontier. A two-staged, semi-parametric Data Envelopment Analysis (DEA) and bootstrapping techniques will be used to develop the models. Technical efficiency shall be estimated in the first stage then regressed on a set of external variables in the second stage and as guided by the works of Similar and $\Upsilon$ approximation of the efficiency distribution in line with the works of Simar and Wilson (2000).

A Data Envelopment Analysis (DEA) is specified as an input-minimizing problem providing a set of scalar measures of efficiency which come in pairs, one set for the input-oriented problem and the other for output oriented problem. We will rely on the two primary scalar measures of efficiency for the input-oriented problem as proposed by Farrell (1957); (i) technical efficiency (TE) which is the proportional reduction in inputs possible for a given level of output in order to obtain the efficient input use, and (ii) allocative efficiency (AE) which reflects the ability of the operator to use the inputs in optimal proportions, given their respective prices.

On bench-marking, we will run econometric models using a cost function, which will show the output–cost relationship for cost minimization. A minimum-cost function will provide the periodic costs incurred by an efficient network company to deliver the network services by modelling the technology in place, the output quantities, the input prices, and the operating conditions of the company [13]. Least-squares-type estimations such as ordinary least squares, corrected ordinary least squares or modified ordinary least squares will be used to estimate the parameters of the cost function for comparable operators under this approach and in line with the work of Richmond (1974). The costs with then be compared with their observed costs benchmarks.
Minimise $\theta_0$

Subject to
$\Theta_0 X = \sum_{j=1}^{n} \Upsilon X_{i1} + S\ i$ Where I = 1,….., M

$Y_{rj} = \sum_{j=1}^{n} \Upsilon_{rj} Y_{i1} + S\ i$ Where I = 1,….., S} Eq1
If the constraint Constraint
$\sum \Upsilon = 1$ is added to equation 1, then input oriented DEA VRS is obtained.

Or Maximise $Z_0$
Max $Z_0 = \frac{\sum_j^n \Upsilon_{i1}}{\sum_j^n \Upsilon_j X_{i1}}$

Subject to
$\frac{\sum_j^n \Upsilon_{rj} Y_{i1}}{\sum_j^n \Upsilon_j X_{i1}} \leq 1$ ……………}Eq 2

Econometricians developed interest in estimating a Production function with an error term. This became more pronounced by Farrel (1957) and reinvigorated in by [3]. Performance assessment, optimisation policy making of electricity distribution are very important issues for the regulators in electricity restructuring and reform. Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) are robust approaches needed to consolidate results of efficiency and bench marking of electricity distribution. They are efficient frontier consisting of the best practice firms and uses it to measure the relative efficiency scores of the less efficient firms. It does not require specification of a production or cost function. These algorithms allow for calculation of allocative and technical efficiencies that can be decomposed into scale, congestion, and pure technical efficiencies (Fa¨ re et al., 1985). An input oriented specification is generally regarded as the appropriate form for electricity distribution units as demand for their services is a derived demand that is beyond the control of utilities and that has to be met[14] (Jamasb and Pollitt, 2003; Jamasb et al., 2004; Giannakis et al., 2005).

Goto and Tsutsui (1998) using the DEA model, measured overall cost efficiency and technical efficiency between Japanese and US electricity utilities, results showed that Japanese utilities were more efficient than US utilities in terms of technical, allocation, and scale efficiency. Fo¨ rsund and Kittelsen (1998) applied DEA efficiency scores to measure the Malmquist productivity index in the Norwegian electricity distribution companies.

Resende (2002) used the non-parametric input-oriented DEA model for evaluation of Brazilian electricity distribution firms. In Resende’s study, potential and difficulties with the implementation of yardstick schemes were discussed. Edvardsen and Fbrsund (2003) studied performance of 122 electricity distributors in the Denmark, Finland, Norway, Sweden, and Netherlands in 1997. They applied the input-oriented DEA model and the Malmquist productivity index and found that Finland electricity distributors had the highest productivity among other countries. Giannakis et al. (2005) applied the DEA model to study service quality of United Kingdom electricity distribution utilities. They found that cost-efficient firms do not necessarily exhibit high service quality and efficiency scores of cost-only models do not show high correlation with those of quality-based models. In other studies, the various models have been applied as alternative and the correlation between these models have been calculated. In spite of this, they have not provided any method for calculating final efficiency score and rank of every unit. Namely, the different models provide the different efficiency scores and ranks, but the combination of these ranks to obtain the final efficiency scores and ranks have not been done.

Estache et al. (2004) applied DEA and econometric methods for performance assessment and ranking of South American electricity units. They found high correlation between different econometrics as well as DEA models. However, there was low correlation between DEA and econometrics models. Jamasb and Pollitt (2003) compared 63 regional electricity distribution utilities in the six European countries.

To calculate efficiency and to consider the effects of choosing the variables and methods, they used ten DEA, and SFA models. In addition to electricity distribution industry, there are many studies about comparison of different models in other industries. Zhu (1998) and Premachandra (2001) used principle component analysis (PCA) as an alternative to DEA. They showed the high correlation between DEA and PCA models. A study has been done by Bifulco and Bretschneider (2001) for estimation of school efficiency with DEA and COLS models. Herrero (2005) compared four different approaches DEA, stochastic production frontier, panel data, and distance function. These methods were applied to the Spanish Trawl Fishery that was operated in Moroccan water. Furthermore, in some studies an integrated DEA–PCA model has been used. Adler and Golany (2001) have used PCA as a data reduction technique to select inputs and outputs.

However, in a few studies, efficiency scores of different models have been combined to obtain the final efficiency scores and ranks. Coelli and Perelman (1999) have applied parametric linear programming (PLP), DEA, and COLS models to investigate technical efficiency in European railways. They have used the geometrical mean of efficiency scores of the combination of the DEA and PLP results for final ranking. As mentioned before, using each of above different models culminates in specific ranking, without considering which model. Other studies involving the use of DEA include:Agrell et al., 2005; Cullmann, 2009, 2012; Forsund and Kittelsen, 1998; Hjalmarsson and Veiderpass, 1992; Iglesias et al. 2010; Jamasb and Pollit, 2003; Kopsakangas-Savolainen and Svento, 2008; Korhonen and Syrjänen, 2003; Weyman-Jones, 1991.

### 4.2.2 The Stochastic Frontier Analysis (SFA)

The SFA has for been popularised by the works of [3]; Lovell, (1993); Greene, (1993). SFA allows estimates of both cost efficiency and production efficiency. The literature related to the SFA model is highly in line with strong policy implementation especially for public utilities (Lovell, 1995). It's therefore employed by different scholars to measure efficiency for different Decision Management Units (DMUs) at different phases within the production and supply chain of DMUs. Such scholars as; [8](Burns & G.Weyman-Jones, 1996); (Hiebert, 2002) have employed SFA specifically for electricity utilities regulation

$C_i = \alpha + \beta_i X + \varepsilon_i$ eq 3

$C_i$ is the cost for firm i
$X_i$ is the matrix of independent variables for the ith firm
$\alpha$ and $\beta$ are parameters of the model
$\varepsilon$ is the error term
The error term is accordingly decomposed into its stochastic and efficiency components as given by Aigner et al (1977).
$C_i = \alpha + \beta_i X + u_{i+Vi}$ eq 4
$U_i \geq 0$ and $V_i$ is unrestricted
The distribution $U_i$ is taken to be half normal [3] truncated normal (Stevenson, 1980) or exponential (Meeusen and van den Broeck, 1977)
The error due to cost inefficiency cannot be observed directly but is generated from the composite error $\varepsilon$.
Panel data estimates examine DMUs' observations over time and the model is estimated as below:
$C_{it} = \alpha + \beta_{it} X + \varepsilon_{it}$ eq 5

$\varepsilon_{it} = U_{it} + V_{it}$

$V_{it}$ capture measurement error and random disturbances resulting from factors beyond the control of the firm.

The one-sided error terms $U_{it}$, represent the increase in cost relative to the frontier due to managerial operating inefficiency given output levels, input prices, and the existing production technology.

In this model, there are different DMUs (N) observed over time (T) for each DMU. If there are no time invariant factors considered, then there is no need for the assumption that the errors are uncorrelated with the variables. Implying that the estimation does not take the assumption ≥ 0 and the estimate of $U_i$ is consistent. Then the model may be estimated using Generalised Least Squares (GLS) or by maximum likelihood Estimation (MLE). Panel data estimates are regressed using natural logs for the variables of consideration for robust outcomes.

$LnC= C(Y_{it}, P_{it}, K_{it}, X_{it}) +u_{it+Vit}$

$Y_{it}$denotesoutput

$P_{it}$ denotes the variable input prices

$K_{it}$denotes the plant capacity

$X_{it}$represents the technology related characteristics of the firm

It's based on random estimates using both cross section data and panel data. However, the conditions for set for the error term for cross section data led to the use of panel data more relevant and reliable, since it allows comparison of DMUs over a longer time period. Panel analysis also has its own shortfalls as it requires data over time which sometimes may not be available. However, panel data has been established to produce results which are more robust for decision making. Initially, a deterministic approach would be used to measure the inefficiencies, but it fell short of separating the technical inefficiency from the purely random shocks of the DMUs. E.g. changes in weather conditions, which have an implication on the costs and output (Burns & G.Weyman-Jones, 1996).

A study conducted by Filipini& Luis Orea (2014), on the applications of stochastic frontier in energy economics established that, this method can both be used for efficiency measures in the energy sector and rebound effects due to improvement in the energy efficiency. In this study, the distribution network of DMUs were analysed using panel data to estimate their robustness. SFA has been used by different scholars to analyse efficiency of distribution networks of the power sector. It's at the distribution phase of electricity that the operational performance is a very key issue of consideration within the power sector and therefore regulation is very crucial for both observed and unobserved heterogeneity [8](Kopsakangas-Savolainen & Svento, 2011)(Khetrapal, Thakur, & Gupta, 2015).

Khetrapal et al, (2015), used SFA to model technical efficiency in the distribution power sector of India. The model used was based on Battese&Coelli (1992) to estimate the production efficiency of 37 regulated electricity distribution DMUs using a cross section data with a Cobb Douglas production function estimated, due to low sample from a cross section. In this analysis inputs were considered as total operating expenditure, total distribution network length, total number of distribution transformers and percentage distribution energy losses. Output variable was electricity delivered to end users. Results indicated that technical efficiency of these firms was relatively high with an average technical efficiency of 81.8%.

Leite, et al., (2020), SFA model was used determine non-technical losses of 41 distribution DMUs, for cost regulation. The technical losses had to be disaggregated from non-technical losses to compel DMUs cater for the cost inefficiency losses through incentivised regulation. The study centred on theft of electricity taken as a major non-technical loss and the magnitude of losses it causes to electricity distribution DMUs in Brazil. SFA was used to set target values for the percentage of non-technical losses. Panel data was used and a translog cost function was employed due to its favourable functional properties and flexibility (Coelli, Rao, O'Donnell, & Battese, 2005) (Behr, 2015). The method was found relevant to estimation of likelihood of occurrences of non-technical losses, hence informative to the National Electric Energy Agency (NEEA), for how to reduce non-technical losses to achieve targets of incentive regulation of electricity regulation by electricity distribution DMUs.

## 4.3 Variables

### 4.3.1 Input data variables

Cost data is defined and synchronised in Uganda shillings where applicable. It is collected and presented on a quarterly basis by ERA. Variables relevant to the study of inputs, include operation and maintenance (O&M) costs, a proxy on wage rate was got by dividing O&M by the number of employees and energy price by dividing O&M by power purchased by distribution companies from UETCL. Vital data on network length was discarded because it had only been recorded for 6 of the 28 series and for very few firms, this a great limitation to the inclusion of this variable. Most of the DMUs had been in existence for the last 7 years and data compilation was complete for the 28 quarters. Ferdsult which exited in 2016 had its assets taken over by UEDCL which makes UEDCL's data complete form as early as 2013 and therefore useable in this study.

### 4.3.2 Output data variables

The examination of output variables for purposes of attaining technical efficiency is very critical, energy units sold, number of customers and energy losses. Energy losses was obtained by computing the difference between energy sold and energy bought for each period.

Table 1: Variable description

| Variable code | Variable Name | Variable description |
|---|---|---|
| ly1 | Total energy sold | Natural log of Total energy sold |
| ly2 | Number of customers | Natural log of Number of customers |
| ly3 | Energy loss | Natural log of Energy loss (kwh) |
| Lw | Wage rate or OPEX per employee | Natural log of Wage rate or OPEX per employee |
| Lep | Cost per kw bought | Natural log of Cost per kw bought |
| lntep_kwh | Total energy produced | Natural log of Total energy produced (kwh) |
| lnemployees | Number of employees | Natural log of Number of employees |
| lnom_millions | Operations and maintenance | Natural log of Operations and maintenance (million) |

# 5.0 Findings and Discussion

## 5.1 Findings Using the DEA model

From the descriptives, there is a positive means value for all the DMUs. The 6 DMUs have an overall average efficiency for the distribution subsector is 90.9% with a declining trend. DMU 1 (KRECs) had an average efficiency score of 79.3%, while DMU 2 (KIL) had 93.4%, DMU 3 (BECs) had while 89% while DMU 4 (PACMECs) had 95.3, DMU 5 (UEDCL) had 87.9% DMU6 (UMEME) had 100%. Therefore UMEME was used to benchmark other distribution companies within the subsector. Summarised in table 2.

Table 2: Summary Descriptive statistics (VRS_TE) for the distribution companies

| Stats | dmu_1 | dmu_2 | dmu_3 | dmu_4 | dmu_5 | dmu_6 |
|---|---|---|---|---|---|---|
| N | 28 | 28 | 28 | 28 | 28 | 28 |
| Mean | 0.793 | 0.934 | 0.890 | 0.952 | 0.879 | 1.000 |
| SD | 0.352 | 0.027 | 0.029 | 0.0256 | 0.188 | 0.000 |
| Min | 0.000 | 0.910 | 0.850 | 0.9200000 | 0.460 | 1.000 |
| Max | 0.970 | 0.980 | 0.930 | 0.9900000 | 1.0000 | 1.000 |

5.2 Using the SFA Model

SFA allows us estimate inefficiency and some determinants of this inefficiency.

5.2.1 Selection of regression factors;

At this stage, the choice was made of variables that characterize the natural indicators of the electricity grid business (electricity distribution), prices for production factors and characteristics of the functioning environment. The regression model factors must meet the following requirements: quantitative measurability. If it is necessary to include qualitative factors in the model, they should be given quantitative certainty (scores, ranks); absence of correlation of factors among themselves and functional connection. For our study input variables remained O&M, Wage rate, Energy Price while output variables were energy sold, energy losses and number of customers.

Table 3: Testing for efficiency

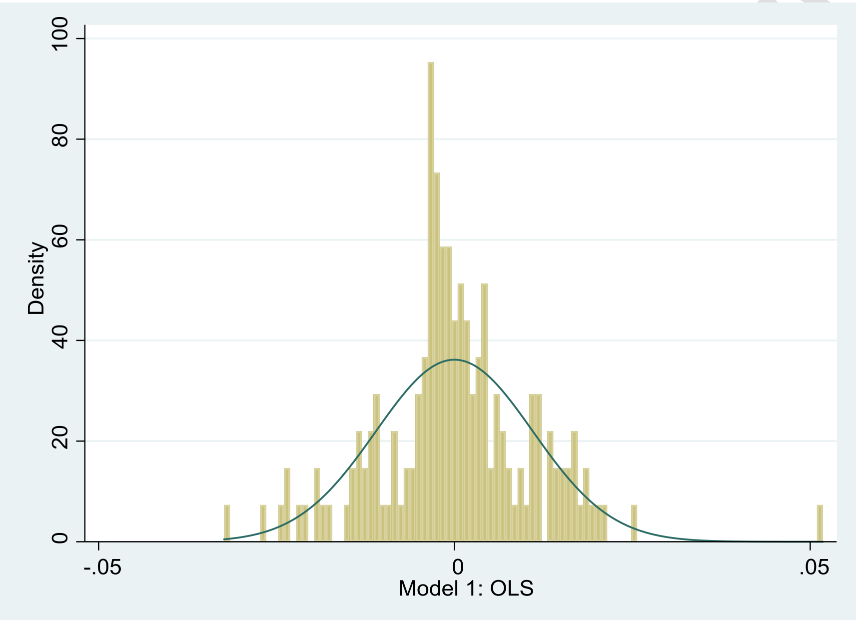
| lnom_millions | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| ly1 | .955 | .091 | 10.55 | 0 | .776 | 1.134 | *** |
| ly2 | .233 | .068 | 3.43 | .001 | .099 | .368 | *** |
| ly3 | .3 | .092 | 3.28 | .001 | .119 | .481 | *** |
| Lw | -.322 | .127 | -2.53 | .012 | -.572 | -.071 | ** |
| Lep | .815 | .138 | 5.89 | 0 | .542 | 1.088 | *** |
| ly1y1 | .123 | .006 | 21.52 | 0 | .112 | .134 | *** |
| ly2y2 | 0 | .002 | 0.19 | .852 | -.004 | .004 | |
| ly3y3 | .081 | .002 | 35.20 | 0 | .076 | .085 | *** |
| Lww | .029 | .013 | 2.17 | .032 | .003 | .055 | ** |
| Lepep | -.059 | .011 | -5.44 | 0 | -.08 | -.037 | *** |
| ly1y2 | -.023 | .008 | -3.01 | .003 | -.038 | -.008 | *** |
| ly1y3 | -.241 | .007 | -35.29 | 0 | -.255 | -.228 | *** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ly1w | -.018 | .013 | -1.36 | .175 | -.044 | .008 | |
| ly1ep | .026 | .011 | 2.41 | .017 | .005 | .047 | ** |
| ly2y3 | .026 | .008 | 3.34 | .001 | .011 | .041 | *** |
| ly2w | -.01 | .014 | -0.74 | .458 | -.037 | .017 | |
| ly2ep | .027 | .011 | 2.48 | .014 | .006 | .049 | ** |
| ly3w | .049 | .009 | 5.76 | 0 | .032 | .066 | *** |
| ly3ep | -.112 | .011 | -10.33 | 0 | -.133 | -.091 | *** |
| Lwep | .01 | .021 | 0.46 | .644 | -.031 | .051 | |
| Constant | -3.568 | .472 | -7.56 | 0 | -4.501 | -2.636 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 6.616 | SD dependent var | 2.438 |
| R-squared | 1.000 | Number of obs | 177 |
| F-test | 154715.317 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -892.646 | Bayesian crit. (BIC) | -825.947 |

*** p<.01, ** p<.05, * p<.1*

Figure 1: Histogram of OLS Residuals




The data is normally distributed and not correlated and with no functional connections among variables meant that there was no need to include qualitative variables.

5.2.2. The form of the cost function

In determining the form of a function form the linear, the Cobb-Douglas function was selected, since costs depend on many factors (the number and cost of factor inputs, cost of equipment, labour costs, supply of electricity, Opex). The form of the cost function is determined for this study and justified over others, which is the bottleneck of the parametric method of estimating costs.

Table 4: Testing for the Functional form – Model in Levels

| lnom_millions | Coef. | St.Err. | t- | p- | [95% | Interval] | Sig |
|---|---|---|---|---|---|---|---|

| | | | value | value | Conf | | |
|---|---|---|---|---|---|---|---|
| ly1 | .497 | .021 | 23.92 | 0 | .456 | .538 | *** |
| ly2 | .062 | .016 | 3.83 | 0 | .03 | .094 | *** |
| ly3 | .425 | .017 | 24.89 | 0 | .391 | .459 | *** |
| Lw | .162 | .03 | 5.40 | 0 | .103 | .221 | *** |
| Lep | .87 | .03 | 29.15 | 0 | .811 | .929 | *** |
| Constant | -.287 | .162 | -1.77 | .078 | -.607 | .033 | * |

| | | | |
|---|---|---|---|
| Mean dependent var | 6.616 | SD dependent var | 2.438 |
| R-squared | 0.997 | Number of obs | 177 |
| F-test | 12328.197 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -213.747 | Bayesian crit. (BIC) | -194.690 |

**** p<.01, ** p<.05, * p<.1*

In Table 4, we test the functional form of the model when variables are in level form to compare them to the model in Table 5, which includes square and cross variables. First, the tiered model results show that all variables were significant at a 5% level, with an F-statistic confirming a correct functional form of the model. In evaluating the model function form of the model, the researcher concludes that the model given in Table 4 has the best parameters and criteria with an Akaike criterion of 213.747, an R-square of 0.997, and a probability of the F-statistic of 0.000. This makes it the best model for this analysis.

Table 5: Testing the Functional form - Model in levels, squares and interactions

| lnom_millions | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| ly1 | .955 | .091 | 10.55 | 0 | .776 | 1.134 | *** |
| ly2 | .233 | .068 | 3.43 | .001 | .099 | .368 | *** |
| ly3 | .3 | .092 | 3.28 | .001 | .119 | .481 | *** |
| Lw | -.322 | .127 | -2.53 | .012 | -.572 | -.071 | ** |
| Lep | .815 | .138 | 5.89 | 0 | .542 | 1.088 | *** |
| ly1y1 | .123 | .006 | 21.52 | 0 | .112 | .134 | *** |
| ly2y2 | 0 | .002 | 0.19 | .852 | -.004 | .004 | |
| ly3y3 | .081 | .002 | 35.20 | 0 | .076 | .085 | *** |
| Lww | .029 | .013 | 2.17 | .032 | .003 | .055 | ** |
| Lepep | -.059 | .011 | -5.44 | 0 | -.08 | -.037 | *** |
| ly1y2 | -.023 | .008 | -3.01 | .003 | -.038 | -.008 | *** |
| ly1y3 | -.241 | .007 | -35.29 | 0 | -.255 | -.228 | *** |
| ly1w | -.018 | .013 | -1.36 | .175 | -.044 | .008 | |
| ly1ep | .026 | .011 | 2.41 | .017 | .005 | .047 | ** |
| ly2y3 | .026 | .008 | 3.34 | .001 | .011 | .041 | *** |
| ly2w | -.01 | .014 | -0.74 | .458 | -.037 | .017 | |
| ly2ep | .027 | .011 | 2.48 | .014 | .006 | .049 | ** |
| ly3w | .049 | .009 | 5.76 | 0 | .032 | .066 | *** |
| ly3ep | -.112 | .011 | -10.33 | 0 | -.133 | -.091 | *** |
| Lwep | .01 | .021 | 0.46 | .644 | -.031 | .051 | |
| Constant | -3.568 | .472 | -7.56 | 0 | -4.501 | -2.636 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 6.616 | SD dependent var | 2.438 |
| R-squared | 1.000 | Number of obs | 177 |
| F-test | 154715.317 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -892.646 | Bayesian crit. (BIC) | -825.947 |

**** p<.01, ** p<.05, * p<.1*

5.2.3 Choosing a method for estimating the cost function

In panel data analysis, the best model for estimating the cost function is determined from the pooled, fixed and random effect models. The fixed effect model is shown in Table 6, with a significant F statistic at a 5% level. The Hauseman test for the most suitable model gives a chi-square test value probability of 0.9915. Hence, we cannot reject the null hypothesis that a random effects model is the most appropriate model.

Table 6: Fixed effects model

| lnom_millions | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| ly1 | 1.249 | .109 | 11.43 | 0 | 1.033 | 1.465 | *** |
| ly2 | .058 | .093 | 0.63 | .533 | -.126 | .243 | |
| ly3 | .47 | .095 | 4.94 | 0 | .282 | .659 | *** |
| Lw | -.097 | .144 | -0.68 | .499 | -.381 | .186 | |
| Lep | .709 | .144 | 4.92 | 0 | .424 | .993 | *** |
| ly1y1 | .11 | .007 | 16.45 | 0 | .097 | .123 | *** |
| ly2y2 | .001 | .002 | 0.36 | .716 | -.003 | .005 | |
| ly3y3 | .082 | .003 | 30.41 | 0 | .076 | .087 | *** |
| Lww | .019 | .013 | 1.43 | .155 | -.007 | .045 | |
| Lepep | -.05 | .01 | -4.98 | 0 | -.07 | -.03 | *** |
| ly1y2 | -.01 | .008 | -1.22 | .223 | -.025 | .006 | |
| ly1y3 | -.241 | .007 | -35.08 | 0 | -.255 | -.227 | *** |
| ly1w | -.029 | .015 | -1.95 | .053 | -.059 | 0 | * |
| ly1ep | .03 | .013 | 2.39 | .018 | .005 | .055 | ** |
| ly2y3 | .021 | .008 | 2.64 | .009 | .005 | .037 | *** |
| ly2w | -.007 | .015 | -0.45 | .656 | -.036 | .023 | |
| ly2ep | .022 | .013 | 1.68 | .096 | -.004 | .048 | * |
| ly3w | .049 | .009 | 5.65 | 0 | .032 | .066 | *** |
| ly3ep | -.094 | .011 | -8.56 | 0 | -.115 | -.072 | *** |
| Lwep | .017 | .021 | 0.81 | .419 | -.024 | .057 | |
| Constant | -6.454 | .803 | -8.04 | 0 | -8.04 | -4.867 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 6.616 | SD dependent var | 2.438 |
| R-squared | 1.000 | Number of obs | 177 |
| F-test | 15699.928 | Prob > F | 0.000 |
| Akaike crit. (AIC) | -931.072 | Bayesian crit. (BIC) | -864.373 |

**** p<.01, ** p<.05, * p<.1*

Table 7: Hauseman test for the most appropriate model

| | Coef. |
|---|---|
| Chi-square test value | 36.844 |
| P-value | .012 |

After a critical Hauseman test analysis for the most suitable model, which confirms the random effects model. The researchers begin by analyzing the final random effects models. These models include; 1) Green 2005b true fixed effects model (exponential), 2) Green 2005b true random effects model (semi-normal)

Table 8: Random effects model is the best model

| lnom_millions | Coef. | St.Err. | t-value | p-value | [95% Conf | Interval] | Sig |
|---|---|---|---|---|---|---|---|
| ly1 | .955 | .091 | 10.55 | 0 | .778 | 1.133 | *** |
| ly2 | .233 | .068 | 3.43 | .001 | .1 | .367 | *** |
| ly3 | .3 | .092 | 3.28 | .001 | .121 | .48 | *** |
| Lw | -.322 | .127 | -2.53 | .011 | -.57 | -.073 | ** |
| Lep | .815 | .138 | 5.89 | 0 | .544 | 1.086 | *** |
| ly1y1 | .123 | .006 | 21.52 | 0 | .112 | .134 | *** |
| ly2y2 | 0 | .002 | 0.19 | .852 | -.004 | .004 | |
| ly3y3 | .081 | .002 | 35.20 | 0 | .076 | .085 | *** |
| Lww | .029 | .013 | 2.17 | .03 | .003 | .055 | ** |
| Lepep | -.059 | .011 | -5.44 | 0 | -.08 | -.038 | *** |
| ly1y2 | -.023 | .008 | -3.01 | .003 | -.038 | -.008 | *** |
| ly1y3 | -.241 | .007 | -35.29 | 0 | -.255 | -.228 | *** |
| ly1w | -.018 | .013 | -1.36 | .173 | -.044 | .008 | |
| ly1ep | .026 | .011 | 2.41 | .016 | .005 | .047 | ** |
| ly2y3 | .026 | .008 | 3.34 | .001 | .011 | .041 | *** |
| ly2w | -.01 | .014 | -0.74 | .457 | -.037 | .016 | |
| ly2ep | .027 | .011 | 2.48 | .013 | .006 | .049 | ** |
| ly3w | .049 | .009 | 5.76 | 0 | .033 | .066 | *** |
| ly3ep | -.112 | .011 | -10.33 | 0 | -.133 | -.091 | *** |
| Lwep | .01 | .021 | 0.46 | .643 | -.031 | .05 | |
| Constant | -3.568 | .472 | -7.56 | 0 | -4.494 | -2.643 | *** |

| | | | |
|---|---|---|---|
| Mean dependent var | 6.616 | SD dependent var | 2.438 |
| Overall r-squared | 1.000 | Number of obs | 177 |
| Chi-square | 3094306.346 | Prob > chi2 | 0.000 |
| R-squared within | 0.999 | R-squared between | 1.000 |

**** p<.01, ** p<.05, * p<.1*

In order to enable a meaningful interpretation of the estimation results, the researcher carries out the test for cross-sectional dependence. We use Frees and Pesaran tests for cross-sectional independence, the test statics of which are 0.234 and -0.633, respectively. The Frees-Q distribution test statistic is below the critical value of the significance level of 0.01, which means that the null hypothesis of cross-sectional independence is not rejected. This result agrees with Pesaran's test, the probability of which is greater than 0.05 level of significance. This finding indicates the presence of heteroscedasticity in the data set.

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In this section we present results of the semi-normal true random effects model from Greene 2005b. Considering 6 DMUs, the results of this model were based on 50 randomized Halton sequences that produced a logarithmically simulated probability of 163.2509. The minimum, mean, and maximum observations per DMU were recorded at 22, 29.5, and 43, respectively. The probability of the model chi-square of 0.0000 indicates that the model is correctly specified and that the interpreted results are therefore meaningful.

Table 9: Greene 2005b true random-effects model

True random-effects model (half-normal)                Number of obs = 177
Group variable: dmu                Number of groups = 6
Time variable: time                Obs per group: min = 22
avg = 29.5

max = 43
Prob > chi2 = 0.0000
Log simulated-likelihood = 163.2509 Wald chi2(5) = 12905.75
Number of Randomized Halton Sequences = 50
Base for Randomized Halton Sequences = 7

| lnom_milli~s | Coef. | Std.Err. | Z | P>z | [95%Conf. Interval] | |
|---|---|---|---|---|---|---|
| Frontier | | | | | | |
| Total energy sold | 0.562 | 0.019 | 29.800 | 0.000 | 0.525 | 0.599 |
| Number of customers | 0.039 | 0.013 | 3.030 | 0.002 | 0.014 | 0.064 |
| Energy loss | 0.295 | 0.018 | 16.390 | 0.000 | 0.260 | 0.331 |
| OPEX per employee | 0.088 | 0.029 | 3.000 | 0.003 | 0.031 | 0.146 |
| Cost per kw bought | 0.873 | 0.027 | 31.960 | 0.000 | 0.819 | 0.926 |
| Constant | 0.866 | 0.299 | 2.890 | 0.004 | 0.279 | 1.452 |
| Usigma_cons | -208.350 | 5.002 | -41.650 | 0.000 | -218.154 | - 198.547 |
| Vsigma_cons | -4.876 | 0.107 | -45.370 | 0.000 | -5.086 | -4.665 |
| Theta_cons | 0.237 | 0.036 | 6.650 | 0.000 | 0.167 | 0.307 |
| sigma_u | 0.000 | 0.000 | 0.400 | 0.689 | 0.000 | 0.000 |
| sigma_v | 0.087 | 0.005 | 18.610 | 0.000 | 0.079 | 0.097 |
| lambda | 0.000 | 0.005 | 0.000 | 1.000 | -0.009 | 0.009 |

The model results are discussed using five boundaries that form the regressors of the cost function. With operations and management as the predicted variable for our panel model, the results show highly significant coefficients at the 0.05 level. A percentage increase in the total energy sold by distribution companies increases their O&M costs by 56.2%. This result is highly significant at the 0.01 level.

We continue to observe that a percentage increase in energy losses significantly increases the operating and maintenance costs of distribution companies by up to 29.5%. A result highly significant at the significance level of 0.01. The estimated results show the same effect pattern for the number of customers, the wages of the employees (OPEX per employee) and the costs per KW purchased with a percentage change in the operating and maintenance costs of 3.9%, 8.8% and 78.3%, respectively.

In the next section, we embark on a detailed discussion of the results presented in the above model.

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## 5.3 Discussion of results

DEA was analysed using DEA- Stata program an input DEA was run. It does not concern itself with functional form and does not test the hypothesis so no statistical tests were run while SFA gave us room to separate random error and inefficiency of the distribution companies, it took into consideration differences in operating conditions of the companies, and allowed room to conduct statistical tests [15].

The examination of service costs enables the Electricity Regulatory Authority (ERA) re-assess the levels of inefficiency among the system operators which informs the decisions to control or minimize increase in tariffs. The research will also inform the relevant government officials on the efficiency levels of the system operators which may lead to policy review. There will be increased awareness of the various types of regulatory capture and the nature of impediment encountered in realizing the targets of the regulatory framework. This should enable the concerned officials to reorganize accordingly. Through increased usage of electricity, the level of manufacturing is boosted, while standards of living could be positively impacted with reference to the beneficiary communities, thereby enhancing entrepreneurial initiatives. In general, the contribution over a period of time should be able to cause an increase in per capita electricity consumption; contribute to a reduction in the share of biomass energy used for cooking and on the overall, contribute to an increase in the share of clean energy used for cooking.

### 5.3.1 Is there technical efficiency in the distribution industry?

A test conducted on the SFA model is to establish whether technical inefficiency exist in the distribution subsector. This is done by putting restrictions on the translog model that $\Upsilon = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$ indicate that energy loss and energy purchased by DMUs constitute the most efficient cost drivers.

This therefore implies that incentive regulation has a positive influence on cost efficiency and tariff setting.

## 6.0 Conclusion and Policy Recommendations

### 6.1 Conclusions

This study has looked at incentive regulation in the electricity distribution subsector with a view of establishing an efficient tariff regime. Based on the findings modelling of incentive regulation in electricity distribution subsector in Uganda using price cap has enhanced investment into electricity infrastructure under long term regulatory contracts. Our study confirms that under the self-selection, regulated firms have no adverse effects on investments and hence improve welfare ceteris paribus [4].

Secondly the reduction in energy losses and energy purchases from transmitter make up the most efficient cost drivers. This explains the fairly stable tariff to the end user that the regulator has capped at an increment not exceeding 6% per quota tagged to some macroeconomic variables of inflation, oil prices and exchange rates

Lastly, tariff regulation has increased efficiency in operations through in improved quality and reliability of power distribution. First and foremost is reduced load shedding, secondly is more reliable power distribution to end users. This improves the overall living conditions of the citizens

### 6.2 Policy Recommendations

Cost input DEA gives recommendation of inefficiencies existing in the way distribution firms cost their operational and maintenance costs which leads to higher tariff. Therefore the regulator should keenly and independently verify the costing of O&M and the way it’s transmitted to the end user tariff. Otherwise this can explain the low rate of investment into grid expansion by the distributors, which ultimately reduces access to end users.

### 6.3 Further Research

Further research should interest itself in understanding how self-selection methods of incentive regulation by regulator on the distribution firms are able to mitigate the problem of regulatory capture.

**Ethical Approval:** This study never involved human subjects and got ethical clearance from relevant authorities

**Consent to Participate:** Since o human subjects were involved, there was no need for consent from participants

**Consent to Publish.** This work has not been presented to a publishing house before and upon acceptance by this journal and will relinquish the consent to publish

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