A Framework for Establishing the Technical Efficiency of Electricity Distribution Counties (EDC) using Data Envelopment Analysis

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ABSTRACT

European Energy market liberalization has entailed the restructuring of electricity power markets through the unbundling of electricity generation, transmission and distribution, supply activities and introducing competition into electricity generation. Under these new electricity market regimes, it is important to have an evaluation tool that is capable of examining the impacts of these market changes. The adoption of Data Envelopment Analysis as a form of benchmarking for electricity distribution regulation is one method to conduct this analysis. This paper applies a Data Envelopment Analysis framework to the electricity distribution network in Ireland to explore the merits of using this approach, to determine the technical efficiency and the potential scope for efficiency improvements through reorganizing and the amalgamation of the distribution network in Ireland. The results presented show that overall grid efficiency is improved through this restructuring. A diagnostic parameter is defined and pursued to account for aberrations across Electricity Distribution Counties as opposed to the traditionally employed environmental variables. The adoption of this diagnostic parameter leads to a more intuitive understanding of Electricity Distribution Counties.

Key Words: Data Envelopment Analysis; Technical efficiency; performance measurement/evaluation, Electricity Distribution.

1. Introduction

The structural adjustment of Electricity Power Systems (EPS) liberalisation over the last 20 years worldwide has seen a significant shift in focus from regulated to a deregulated environment to enhance technical efficiency, financial viability and guard against the threat dwindling fossil fuel resources coupled with increasing fuel prices. The underlying rational behind these reforms is to foster a shift from an inefficient monopolized vertically-integrated industry to an efficient competitive electricity market environment (Trevino, 2008). The transmission and distribution networks of a nation's electricity system are natural monopolies, and as such are less affected by the recent EPS deregulation. However, as electricity policy thinking has altered with private sector participants in the generation sector, regulatory reform and incentive regulation of electricity distribution utilities have become more common (Farsi et al., 2007). Implementing benchmark performance measurement and assessing technical efficiency of electricity distribution utilities[1] has seen extensive research in recent years with DEA at the forefront of this research. Effective regulation in terms of electricity distribution, network access, network interconnection and delivery prices, network investment and network service quality are paramount components of successful EPS liberalisation programs worldwide (Joskow, 2008). Data Envelopment Analysis (DEA) concepts were first introduced by Farrell (1957) but later the approach was pioneered Charnes et al., (1978) that has led to the foundations of a literature field that has formed at the interface of operational research and economics. This paper employs a DEA non-parametric methodology to establish a frontier or best practice benchmark measure of the relative performance of twenty-six Electricity

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[1] We adopt the umbrella term utilities to refer to electricity distribution organizations, companies, districts, centers, zones, areas, regions, counties and operators.

Distribution Counties (EDC)[2] in Republic of Ireland (ROI). The aims and objectives of this research are: 1) to establish technical efficiency and differentiate between efficient and inefficient EDCs by implementing the DEA benchmarking approach to electricity distribution in the ROI; 2) to propose specific directions to enhance operational management and to improve the utilisation of resources within the inefficient EDCs and 3) to investigate the possibility of reorganising and amalgamation of existing EDCs to improve efficiency of electricity supply networks distribution system based on geographical convenience.

The research conducted in this paper adds to the field of research in evaluating the technical efficiency of power systems. Firstly, in its application to the test system - all island SEM, secondly, in its employment of input-output parameters and alternative combinations to develop new models based on the DEA techniques for the efficiency assessment. The input-output parameters, alternative combinations and constructed DEA models are the salient contributions of the paper. A significant contribution of the current research is the wind generating regional DEA model employed in the National level efficiency context as it provides a new framework for evaluating wind generation on a regional basis.

2. Single Electricity System

Since 1988, the Irish electricity market has adopted a process of liberalization, prior to this Electricity Supply Board (ESB) operated as a vertically integrated state owned monopoly. The liberalization process has occurred in phases with sections of the

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[2] Electricity Distribution Counties refer to autonomous regions, or municipalities located on the island of Ireland.

market being progressively opened for competition, with the market entirely open since 2004. The Northern Ireland Authority for Utility Regulation (NAIRU) and the Commission for Energy Regulation (CER) commenced on the 1st November 2007 governance of the Single Electricity Market (SEM). The SEM is an All-Island cross-border electricity market incorporating both the Republic of Ireland (ROI) and Northern Ireland (NI). The SEM initiative established a wholesale electricity market for the island, which subsequently formed the All-Island Market for Electricity (AIME). In 2008, it had 2.5 million electricity customers in total, 1.8 in ROI and 0.7 million in NI (Conlon, 2010). As a centralized gross mandatory pool, all electricity in SEM is traded through a market clearing mechanism based on generators bidding their Short Run Marginal Cost (SRMC) and receiving the System Marginal Price (SMP) (Nepal and Jamasb, 2011). The SEM is operated and administered by the Single Electricity Market Operator (SEMO), which is a contractual joint venture between Eirgrid and the Systems Operator for Northern Ireland (SONI), the transmission system operators in the ROI and NI respectively (both are Independent System Operators (ISO)). The distribution systems operators (DSO) of ROI and NI are owned and operated by ESB Networks and Northern Ireland Electricity (NIE) respectively. The SEM market design has features reminiscent of markets in other jurisdictions (most notably Nordpool, the Eastern Australian market and the former British pool) but is a unique dual currency inter-jurisdictional market (Conlon, 2010). The SEM represents the first synchronous system of electricity system of its kind in the world. The transmission network consists of 6529 km of 400/220/110kV overhead lines and 1083 km of 220/110/38kV underground cables. Due to ROI widely dispersed and significant rural population, the electricity distribution network is typically characterised by long length of 38kV (138977km) and medium voltage

(20600km) overhead lines with low customer density of 12 per km (Walsh, 2006). These unique characteristics provide an interesting market to study in terms of efficiency.

Table 1 Overview of the Electricity Sector market operators in the ROI and NI

	Republic of Ireland			**Northern Ireland**		
Market Segment	**Owner**	**Operator**	**Regulator**	**Owner**	**Operator**	**Regulator**
Generation	ESB and others	ESB and others	CER	ESB and others	ESB and others	NIAUR
Transmission System	ESB	Eirgrid	CER	NIE	SONI	NIAUR
Distribution System	ESB Networks	ESB Networks Ltd	CER	NIE	NIE	NIAUR
Suppliers	N/A	Various	CER	N/A	Various	NIAUR

The EU Third Energy Package under Directive 2009/72/EC provides three unbundling models for achieving the separation of transmission from generation and supply activities (Groenendijik, 2009). Ireland currently does not comply with any of the proposed models as Eirgrid is licensed by the CER to act as transmission system operator (TSO) and is responsible for the operation and development of the transmission grid while ownership of the transmission asset remains with ESB, responsible for the maintenance and construction of the system. The restructuring of the Irish electricity market is inevitable under the EU Directive 2009/72/EC. Further restructuring of the distribution network is anticipated with ESB networks National plan envisaging the disentanglement of the national electricity distribution network into 26 zones (ESB, 2009). As of 2012, data relating to the technical efficiency of electricity distribution is only available on a county basis. The registered capacity of the SEM is 11,388MW with thermal plants contributing 84% (9,535MW), wind 11% (1,331MW), pumped storage 3% (292MW) and hydro 2% (216MW). The All-Island fuel mix for 2008 consisted of 61% Gas, 7% Peat, 11% Renewables, 17% coal, 4% Oil, and 1% other. There is a growing trend evident since 2005 of an increase in contributions of Peat, Gas and Renewables at the expense of Oil and Coal (CER, 2009). The Annual Energy Flow of the SEM in GWhs for 2008 consisted of 29,981 generated, 26,677 from the transmission system, with the distribution network consuming 18714. The total customer sales for 2008 were 26,194, with DSO contributing 24,043 and TSO 2150 (Niall, 2012). ESB Networks is the licensed owner of the electricity distribution system assets whilst ESB Networks Limited is the licensed distribution system operator responsible for the planning, development, construction, operation, maintenance and connection to the electricity distribution system. ESB Networks Limited is also responsible for the installation, maintenance and reading of electricity meters. Numerous countries are employing incentive regulation to promote efficiency improvement in electricity transmission and distribution utilities (Jamasb and Pollitt, 2001).

3. Literature Review on Electricity Distribution Efficiency Measurement

DEA has long been established as an advanced mathematical methodology for benchmarking and measuring efficiency a set of homogenous entities called Decision Making Units DMUs (Emrouznejad et al., 2008; Zhou et al., 2008, Cook and Seiford, 2009). DEA models have been adopted and effectively to assess the optimal production of a wide variety of goods and and services including agriculture, transport, waste management and in particular the energy sector (Sarkis and Weinrach, 2001; Bevilacqua and Braglia, 2002; Vázquez-Rowe et al., 2012; Lui and Wen, 2012; Simões et al., 2012; Caulfield et al., 2013; Zhou et al., 2014; Omrani et al., 2015). Since the 1980's DEA has been used to measure the relative performance of electricity utilities. The adoption of DEA to electricity power systems has been extensive as it accommodates the efficiency measurement of multiple outputs and multiple inputs without pre-assigned weights and where no functional form is pre-established but one is calculated from the sample observations in an empirical way (Murillo-Zamorano, 2004). These characteristics are particularly relevant when investigating, evaluating and modelling the performance of electricity distribution utilities. Fare et al., (1983) pioneered research in this area when they measured the efficiency of electric plants in Illinois (USA) between 1975 and 1979, in order to relate the efficiency scores obtained to the regulation of the sector. Their findings indicate that regulation does not automatically result in efficient operation of electric utilities, nor does it result in consistent performance across plants. The relative efficiency of electricity distribution utilities has seen extensive research worldwide in the last decade due to the restructuring of electricity energy markets, particularly with the introduction of regulation, privatisation and trade liberalisation in numerous countries (Santos et al., 2010). Weyman-Jones, (1991, 1995) measured the productive efficiency of 12 area electricity boards in England and Wales before and after their privatization in 1990. Less than half of the area boards were technical efficient and wide divergences exist in their performance. Weyman-Jones (1995) finds there are numerous practical issues need to be resolved dangers of market collusion, regulatory commitment exist. Militios (1992) employed DEA to evaluate the efficiency of 45 distribution districts of the Greek Public Power Corporation (PPC), adopting various models to explore the effects of geographic region, size and grid sparsity on the results, concluding urban areas attain higher efficiency scores than sparse populated regions. Numerous studies have focused attention on the impact of ownership on the efficiency of distribution utilities with conflicting results. Pollitt (1995), Hjalmarsson and Veiderpass (1992) conclude there exists no significant difference between public and privately owned electricity distribution utilities in terms of technical efficiency. In contrast to this Bagdadioglu et al., (1996) and Kumbhakar and Hjalmarsson (1998) find private ownership of electric utilities leads to greater efficiency performance as opposed to public ownership. Lo et al., (2001) and Chien et al., (2003) investigate the efficiency of electricity distribution districts and service centers associated with the Taiwan Power Company (TPC) respectively. Both studies propose district and service center reorganization to increase efficiency. In both cases higher efficiency is attainable through reorganization. Yang and Lu (2006), Chen (2002) also investigate Taiwan’s electricity distribution sector in a rural versus urban setting find on average technical efficiency to be greater for urban areas as a result of the geographical dispersion of customers. They recommend including an environmental variable in the DEA analysis to account for these differing electricity distribution environments (i.e. environmental variable)[3]. Jha et al, (2011) analyze the performance of the electricity distribution system in Nepal using weight restriction DEA techniques to measure efficiency. Again as with previous examples in the literature electricity distribution centre reorganization and directions for improvement are put forward. Pahwa et al, (2003) present a method for benchmarking the performance of the 50 largest electric distribution utilities in the U.S based on DEA. The results analyze performance efficiency, inefficient utilities, input-output variables and sensitivity-based classification of utilities. They conclude inefficient utilities can adopt and develop strategic plans to improve performance. For an extensive review on applications of DEA on electricity distribution systems the reader is referred to (Santos et al., 2010; Jamasb and Pollitt, 2001; Reyes and Tovar, 2009; Doraisamy, 2004; Kherikhah et al., 2013; de Souza et al., 204).

4. Non-Parametric Data Envelopment Analysis (DEA) Efficiency Measurement

DEA is a mathematical programming non-parametric technique, applied in performance measurement and benchmarking (Liu and Wen, 2012). It has been applied in a range of empirical settings to identify technical inefficiencies of DMUs and provide targets for improvement for inefficient DMUs. Charnes et al., (1978) pioneered the DEA approach, entitled Charnes-Cooper-Rhodes (CCR) model where a frontier based efficiency measurement is developed under Constant Returns to Scale (CRS). DMU’s operating on the constructed efficiency frontier are Pareto-optimal efficient units and DMU’s not on the efficiency frontier are inefficient. The

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[3] Environmental variables refer to environmental influences, non-discretionary, exogenously fixed input or output factors that affect DEA efficiency.

formulation of the primal form of the CCR linear programming model to measure total technical efficiency (TTE) for each DMU is given as:

Equation 1

$$\text{MAX DMU}_k = \theta_k = \frac{\sum_{r=1}^{m} u_{rk} y_{yk}}{\sum_{r=1}^{n} v_{jk} x_{jk}}$$

$$\text{Subject to: } \frac{\sum_{r=1}^{m} u_{rk} y_{rz}}{\sum_{r=1}^{n} v_{jk} x_{jz}} \le 1;\ \text{z=1,............, s;}$$

$$u_{rk} v_{jk} \ge 0;\ \text{r = 1,........m; j = 1,......, n;}$$

In this formulation, there are *m* outputs produced, *n* input resources, and *s* DMUs or EDCs. *kth* DMU being evaluated in the set of z = 1,……, s DMU's, with an efficency measure of $\boldsymbol{\theta}_k$ rated relative to all other DMU's. The output data y_{rk} is the value of output *r* for DMU_k, while x_{jk} is the input *j* for DMU_k during the period of observation. u_{rk} is the coefficient or weight assigned to outputs r computed in the solution to the DEA model, similarly v_{rk} is the coefficent of weight assigned to inputs *j* computed in the DEA model. All weights are restricted and non-negative". The measure of efficiency is defined as the maximisation of the ratio of weighted linear combinations of outputs to the weighted linear combinations of inputs, subject to the constraint that the efficency score obtained for each DMU cannot exceed one. The efficiency score is bounded between zero and one. The above CCR model is a fractional programming model and can be transformed to a linear programming problem if either the denominaror or numerator of the rairo is forced to equal one (Ramanathan, 2005).

Equation 2

$$\text{Max DMU}_k = \theta_k = \sum\nolimits_{r=1}^{m} u_{rk} y_{rk}$$

$$\text{Subject to: } \sum\nolimits_{r=1}^{m} u_{rk} y_{rz} - \sum\nolimits_{r=1}^{n} v_{jk} x_{jz} \le 0;\ \text{z = 1,......,s;}$$

$$\sum\nolimits_{r=1}^{n} v_{jk} x_{jk} = 1$$

$$\mu_r, v_j \ge \varepsilon > 0; \text{r = 1,......,m; j = 1,..., n;}$$

where ε is an infinitesimal positive number. This form is known as the multiplier form of the linear programming problem. The dual problem of the multiplier is solved for computational convenience and examining the slack variables.

Equation 3

$$\text{Min } \theta_k - \varepsilon\Big(\sum\nolimits_{j=1}^{n} \overline{s}_{jk} + \sum\nolimits_{r=1}^{m} \overset{+}{s}_{rk}\Big)$$

$$\text{Subject to: } \sum\nolimits_{z=1}^{s} x_{jz}\lambda_z + \overset{-}{s}_{jk} = \theta x_{jk} \quad \text{j = 1, 2,......, n;}$$

$$\sum\nolimits_{z=1}^{s} y_{rz}\lambda_z - \overset{+}{s}_{rk} = y_{rk} \ \ \text{r = 1, 2,......, m;}$$

$$\lambda_z, \overset{-}{s}_{jk}, \overset{+}{s}_{rk} \ge 0 \ \ \text{z = 1, 2,......,s.}$$

where θ_k is the scalar efficiency measure of DMY "k" rate relative to all other DMU's $\overline{s}_{jk}$ slack variable for input constraint, s^{+}_{rk} slack variables output constraints, which are both constrained and to be non-negative, and λ_z is the dual coefficient or weight assigned to DMU's. Efficiency scores are constructed by measuring how far a DMU is from the frontier. DEA establishes an efficiency score for each DMU relative to other DMUs in the database that demonstrates what the *"most efficent"* DMUs are and by how much less efficent DMUs fall short (Onut and Soner, 2007). Banker et al, (1984) constructed the Banker-Charnes-Cooper (BCC) model under Variable Returns to Scale (VRS) environment producing an efficiency frontier measure of technical efficiency. The formulation of the BCC model is achieved by adding the convexity constraint $\sum_{z=1}^{s} \lambda_z = 1$ to (3). The BCC model allows for further analysis of the CCR.

efficiency score by decomposing it into technical and scale efficiency components thereby permitting an investigation of scale effects (Thakur et al., 2006). Scale efficiency is a ratio of the two efficiency scores obtained in the CCR and BCC models and is not greater than one (Cooper et al., 2007).

Equation 4

$$\text{Scale efficiency} = \theta_{CCR} / \theta_{BCC} \quad ^{\theta_{CCR}/\theta_{BCC}}$$

where θ_{CCR} and $^{\theta BCC}$ are CCR and BCC efficiency scores of DMU respectively. The scale efficiency represents the proportion of inputs that can be further reduced after pure technical in efficiency is eliminated if scale adjustments are possible. Environmental, exogenous or non-discretionary variables are those that are not under the direct discretionary control of the DMUs or EDCs in this case. The previous illustrated DEA procedures implicity assume DMUs control all variables, failing to account for environmental variable influences.

Examples from DEA electricity distribution literature include inverse density index, customer and network density, customer dispersion. Banker and Morey (1986) whose formulation follows, develop a single stage approach to account for non-discretionary environmental variables (quasi-fixed inputs and/or outputs whose magnitured are temporarilly constrained by contractual arrangements).

Equation 5

$$\text{Min } \theta_k - \varepsilon\left(\sum_{j\in I_D}^{n} s^{-}_{jk} + \sum_{r=1}^{m} s^{+}_{rk}\right)$$

$$\text{Subject to: } \sum_{z=1}^{s} x_{jz}\lambda_z + s^{-}_{jk} = \theta x_{jk} \quad j \in I_D;$$

$$\sum_{z=1}^{s} x_{jz}\lambda_z + s^{-}_{jk} = x_{jk} \quad j \in I_{ND};$$

$$\sum_{z=1}^{s} y_{rz}\lambda_z - s^{+}_{rk} = y_{rk} \quad \text{r=1,2,.....m;}$$

$$\lambda_z, s^{-}_{jk}, s^{+}_{rk} \ge 0 \quad \text{z = 1, 2,...., s.}$$

The software package DEA-Solver version 11 was used to estimate the DEA models presented in this paper.

5. Research Framework and Data Selection

Ireland is 81,638 km^2 separated politically into the Republic of Ireland (ROI) and Northern Ireland (NI). The island of Ireland consists of 32 counties[4], 26 in the ROI and 6 in NI. These counties are further divided into four provinces Leinster, Munster, Connaght and Ulster (see map Figure 1). This paper utilizes a dataset of 26 Electricity Distribution Counties (EDC) associated with ESB networks company in the ROI. Our empirical study analyses the technical efficiency of ESB networks interconnected distribution system, each EDC responsible for medium and low voltage electricity distribution to a particular geographic region in the ROI.

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[4] Counties of the island of Ireland refer to sub-national divisions adopted for the purpose of geographic demarcation and local government.

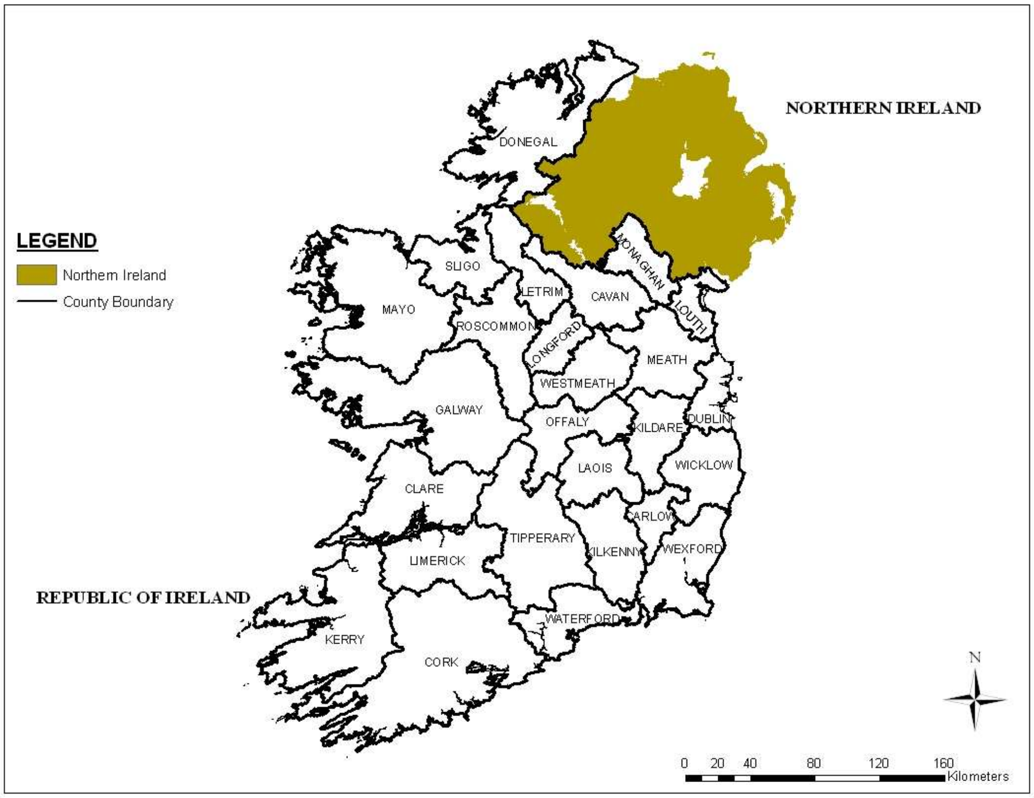

Fig. 1 Electricity Distribution Counties (EDCs) in the Republic of Ireland

Each EDC, autonomous region, or municipality is considered as a Decision Making Unit (DMU) under DEA analysis. The year under observation is 2008, the first full operational year of the All-Island Single Electricity Market (SEM). The use of annual data reduces the influence of seasonal effects. Five inputs and four outputs extensively used in similar studies that use DEA are employed in this study. The input and output variables adopted in this study are all expressed in physical units. Keeney and Rafiffa (1993) state a desirable set of measurement factors should be complete, decomposable, operational, non-redundant, and minimal. The adopted five model analysis incorporates internationally recognized variables judiciously to capture the essence of the electricity distribution process associated with ESB networks. The database developed for DEA analysis in this study has been sourced predominately through collaborating and consultation with ESB networks. Other sources of variable information include public sector databases SEAI, (2008), and central statistics database (CSO, Ireland). The definition and descriptive statistics of the variables adopted in the analysis are given in Tables 2 and 3.

Table 2 Definition of Variables Inputs (X) Outputs (Y)

Inputs (X) Outputs (Y)	**Measurement**
X1: Labour	Numerical Number
X2:Distribution Length	Kilometre (km)
X3: Transformer Capacity	Megavolt Ampere (MVA)
X4: Categorical Variable	[0, 1]
Y1: Gross Energy Consumption	Megawatt Hour (MWh)
Y2: Net Energy Consumption	Megawatt Hour (MWh)
Y3: No of Customers	Numerical Number
Y4: Service Area	km^2
Y5: Diagnostic Parameter (Industrial Output)	Numerical Number
Y6: Environmental Variable (Customer Line Density)	Numerical Number/per km

X1 Labour – This incorporates only the number of ESB network employees within each EDC irrespective of their status. It includes operation and maintenance, technical, non-technical as well as administrative employees.

X2 Distribution Network Length – This represents the 38kV, Medium (MV) and Low Voltage (LV) distribution network measured in (km) per EDC.

X3 Transformer Capacity – It is the total capacity of transformers connected to the distribution system for the distribution purpose. This is measured in MVA.

X4 Categorical Variable – Use of categorical variable (0, 1) to represent if EDC is composed of a city or urban centre.

Y1 Gross Energy Consumed – This represents the total energy utilized or consumed within the EDC area. It is expressed in (MWhs).

Y2 Net Energy Consumed – This is Y1 Gross Energy Consumed less the distribution losses incurred within the area served by the EDC. Losses are included as a proxy for the technical quality of the grid or the service quality of the grid. It is expressed in (MWhs).

Y3 Number of Customers – It is the total number of connection points to supply the customers. Customers are not differentiated based upon their categories. The number of customers captures the number of nodes the utility must supply.

Y4 Service Area (km^2) – The service area encapsulates the geographical differences among electricity distribution counties. Both the number of customers and the km^2 of service area represent customer area density. The service area is employed an output variable to reflect the difficulty of meeting customer services over a less densely populated area.

Y5 Diagnostic Parameter – The industrial output per EDC represents the selling value of goods actually produced in the year, as reported by the businesses themselves, irrespective of whether sold or put into stock (CSO, 2008).

Y6 Environmental Variable – The customer line density defined as the number of customers per (km) length of distribution network.

Table 3 Descriptive Statistic of Variables of the EDCs

Inputs (X) Outputs (Y)	Number of EDCs	Mean	Standard Deviation	Minimum Value	Maximum Value
X1	26	167	102	58	536
X2	26	6186.84	3793.21	2145	19858
X3	26	22699.79	29495.09	4826.05	157025.8
Y1	26	306753.9	398582.3	65217	2121970
Y2	26	284054.13	369087.18	60390.94	1964944.22
Y3	26	84099	106846.7	17925	565110
Y4	26	2703.46	1727.09	826.13	7499.95
Y5	26	3670943.07	6659936.3	161190	31274436
Y6	26	12.69	10.26	7	62

Model Orientation

DEA efficiency analysis can be determined by adopting input-minimizing or output-maximizing models. *Input oriented model* - model whose objective is to minimize inputs while producing at least the given output levels. *Output oriented model* - model that attempts to maximize outputs while using no more than the observed amount of any input (Cooper et al., 2007). Traditionally, efficiency analyses in the electricity sector assume the output fixed in a market with the legal duty to serve all customers in a predefined service territory (Von Hischhausen et a.l, 2009). Because EDCs are unable to control the amount of energy consumed (consumer demand) and the environmental factors, and because the researchers wanted to assess the technical efficiency of EDC's under the objective of minimizing the amount of resources utilised, input-oriented models were adopted.

Model 1 (Comprehensive): This is the base model and all other models are a variation the inputs and outputs employed. This model is designed to encapsulate the overall variables impacting on the technical efficiency of electricity distribution in ROI. This is an extensive model including four inputs and three outputs. This model is an amalgamation of the first two models to represent the overall operational characteristic of EDC's under analysis. Table 4 outlines the various models employed in the analysis.

Model 2 (Basic Traditional): From the extensive DEA literature, the choice of input/output variables for electricity distribution benchmarking needs to account for international experience and data availability. Jamasb and Pollitt (2003) review 20 benchmarking studies in terms of electricity distribution efficiency establishing the number of employees[5] (labour), network length[6] (capital) and transformer capacity (peak load) the most frequently used input variables while output measures being energy delivered, number of customers. There is no pre-defined set of variables to assess the performance of electricity distribution utilities and each study is case specific (Giannakis et al., 2005). The basic model incorporates the above mentioned variables. Similar input/output combinations have been employed by (Azadeh et al., 2009a, 2009b, Sadjadi and Omrani, 2008).

Model 3 (Quality Service): The inclusion of distribution losses as a proxy for the technical quality of the grid or the service quality of the grid establishes the quality of

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[5] Using the number of employees imposes an implicit assumption that the average number of working hours is similar across firms. Therefore, total hours worked may be a better measure for labor input. However, data availability required the use of this variable

[6] Estache et al, 2004 state network length can be employed as an input or output variable, but the author uses it as a measure of input capital.

electricity distribution service offered within each EDC's. Distribution losses are a source of inefficiency and are the difference between the electricity required and the electricity distributed to end-users. These losses can be of technical and non-technical nature (measurement error and unmetered supplier). A reduction in costs to the consumer requires a reduction in both forms of losses and contributes to a reduction in CO^2 emissions (Ramos-Real et al., 2009). The Gross energy consumption less the distribution losses gives Net energy consumption (MWh). The input/output combinations in model 3 have been successfully adopted by (Ramos-Real et al., 2009, Pacudan and de Guzman, 2002, Von Hirschhausen, 2006).

Discretionary models of DEA assume that all inputs and outputs are discretionary, i.e., controlled by the management of each DMU and varied at its discretion. In any realistic situation, however, there exists external exogenously fixed factors or non-discretionary inputs/outputs that are beyond the control of a DMUs management that influence the performance of EDCs. The final two models attempt to acknowledge and account for these influential factors. EDCs may not be operating under equivalent environmental conditions; that is certain EDCs may operate in a more favorable position in terms of population density, topography, geography, industrialized area.

Model 4 (Urban): Adapted from (Miliotis, 1992), a categorical variable is introduced to account for EDCs that contain an urban centre/city. Two groups are formed Urban Distribution Counties (UDC) that contain Irish cities and Rural Distribution Counties (RDC) that do not. Two DMU groups are formed one containing all 26 EDCs and from this group the DEA efficiency scores of UDCs containing a city are calculated; the second group excludes the UDCs containing a city leaving 21 RDCs. The DEA efficiency scores of the remaining RDCs without a city are calculated. This is equivalent to introducing a categorical variable (Cooper et al., 2007).

Model 5 (Diagnostic): Given the nature of the Irish Electricity market and the variance in usage across the country, a diagnostic parameter was chosen to highlight county differences. Non-discretionary models with traditional environmental variables such as inverse density index, customer and network density, and customer dispersion were employed with conflicting results. The industrial output variable was incorporated into Non-discretionary model to account for differences amongst EDCs in terms of electricity characteristics, geography. To the authors knowledge this variable has not been employed in DEA literature in a similar context to this research. This model incorporates all the variables in the comprehensive model whilst adding a non-discretionary variable to measure each EDC's Industrial output. This additional variable is in thousands of Euro and represents the selling value of goods produced within EDCs, as reported by the businesses themselves, it is thought this variable will represent the different geographical energy configuration across EDC Electricity Distribution Counties of ESB networks. This data was extract from a CSO[7] (2008) survey entitled "Census of Industrial Production".

Model 6 (Environmental) This model includes non-discretionary models employing the traditional environmental variable customer density, to account for differences across EDCs. This model is similar to model 5 in terms of inputs/outputs employed differing only in the variable included to account for different electricity distribution characteristics across EDCs. A comparison with model 5 is therefore sought.

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[7] The Central Statistic Office perform the duties of collection, compilation, extraction and dissemination for statistical purposes of information relating to economic, social and general activities and conditions in the Republic of Ireland.

Table 4 Model specification and variables employed for analysis

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Inputs						
X1: Labour	✓	✓	✓	✓	✓	✓
X2:Distribution Length	✓	✓	✓	✓	✓	✓

X3: Transformer Capacity	✓	✓		✓	✓	✓
X4: Categorical Variable				✓		
Outputs						
Y1: Gross Energy Consumption		✓				
Y2: Net Energy Consumed	✓		✓	✓	✓	✓
Y3: No of Customers	✓	✓	✓	✓	✓	✓
Y4: Service Area	✓		✓	✓	✓	✓
Y5: Diagnostic Parameter					✓	
Y6: Environmental Variable						✓

Correlation analysis of input and output variables

The relationship between inputs/outputs should be positively correlated (Luo and Donthu, 2001). The correlation relationship between input/output variables is statistically verified using Pearson's correlation. The greater the value of the correlation coefficient, the stronger the relationship between two variables is. The correlation coefficients from the input/output matrix are presented in Table 5. It can be concluded that there is a strong relationship between labour and distribution length with Pearson’s of 0.974 similarly the Tables illustrates there is a weak relationship between labour and customer density 0.152. The assumption of an “isotonicity” relationship between input and output factors is satisfied (Charnes, 1985). That is, a requirement that the relationship between inputs and outputs not be erratic. Increasing the value of any input while keeping other factors constant should not decrease any output but should instead lead to an increase in the value of at least one output. Dyson et al., (2001) state this is achieved when increased inputs reduces efficiency whilst increased output increases efficiency. Also, a desirable property of evaluation method is its discriminating power as a summary measure. Data selection and model validation according to Boussofiane et al., (1991) requires that the minimum number of DMU observations (EDCs) is equal to, or larger than, the product of the number of inputs and outputs. Cooper et al., (2001), Golany and Roll, (1989) also state the number of DMU’s should be three times the sum of the input/output factors. All the models adopted, in this paper satisfy both of these conditions 26 EDCs $\geq$ (3 x 4) or 3(3 + 4). Therefore the proposed DEA models are of high construct validity.

Table 5 Correlation Coefficient between input and output variables

	X1: Labour	X2: Distribution Length	X3: Transformer Capacity	Y1: Gross Energy Consumed	Y2: Net Energy Consumed	Y3: No of Customers	Y4: Service Area	Y5: Industrial Output	Y6: Customer Density
X1: Labour	-								
X2:Distribution Length	.974**	-							
X3:Transformer Capacity	.901**	.90**	-						
Y1:GrossEnergy Consumed	.961**	.951**	.969**	-					
Y2: Net Energy Consumed	.961**	..961**	.969**	.958**	-				
Y3: No of Customers	.969**	.969**	.958**	.995**	.997**	-			
Y4: Service Area	.934**	.934**	.785	.840	.840	.857	-		
Y5: Industrial	.790**	.790**	.871**	.904**	.904**	.888**	.573**	-	

Output									
Y6: Customer Density	.571*	.571*	.729**	.702**	.702**	.703**	.490	.644*	-

Note: ** Denotes Correlation is significant at the 0.01 level, * Denotes Correlation is significant at the 0.05 level

6. Empirical Results and Discussion

Model 1 (Comprehensive): Analysis and Improvement Directions for Inefficient EDCs

The relative efficiency value of the CCR model is the overall efficiency of the EDCs. If the efficiency value equals 1, the DMU is efficient; if it is less than 1, the evaluated EDC is inefficient (Cooper et al., 2007). The CCR model exhibits constant returns to scale assumption and measures the overall efficiency for each unit, specifically by aggregating pure technical efficiency and scale efficiency into one value. The BCC model with variable returns to scale relates to pure technical efficiency accountable to management skills and establishes scale effects. These results are discussed in the next section. The dual linear programming formulations of the CCR and BCC models were run 26 times, i.e one for each DMU or EDC. The results of CCR model analysis indicate that 21 EDCs are inefficient, with only 5 EDCs operating on the efficiency frontier (Westmeath, Offaly, Laois Dublin, Letrim).

Table 6 Individual efficiency scores of EDCs and returns to scale: Model 1

EDC County Regions	**TTE**	**PTE**	**TTE/PTE**	**RTS**	**%**	**%**	**%**	**%**	**%**	**%**
					X1	**X2**	**X3**	**Y2**	**Y3**	**Y**
Donegal	91	99	91	DRS	-9.04	-9.04	-9.04	21.06	0	0
Cavan	63	67	94	DRS	-37.01	-37.04	-37.01	0	0	1.9
Monaghan	71	96	74	IRS	-28.58	28.71	-28.58	41.31	0	0
Letrim	100	100	100	CRS	0	0	0	0	0	0
Sligo	95	96	99	DRS	-5.27	-4.92	-4.92	19.26	0	0
Roscommon	86	90	96	DRS	-14.25	-14.18	-47.40	0	5.71	0
Mayo	98	100	98	DRS	-1.68	-1.81	-1.68	58.46	32.7	0
Galway	82	100	82	DRS	-18	-18.03	-33.86	1.35	0	0

Clare	93	99	94	DRS	-7.13	-7.27	-47.75	4.89	0	0
Limerick	72	76	92	DRS	-27.53	-27.63	-35.28	0	0	0
Tipperary	74	84	88	DRS	-26.07	-26.07	-26.07	17.25	0	0
Kerry	83	90	92	DRS	-16.79	17.05	18.14	20.13	0	0
Cork	70	100	70	DRS	-30.05	-30.15	30.05	7.21	0	0
Waterford	89	90	98	DRS	-11.72	-11.49	-11.49	5.14	0	0
Carlow	73	100	73	IRS	-26.82	-26.81	-26.81	0	2.89	0
Dublin	100	100	100	CRS	0	0	0	0	0	0
Kildare	65	65	100	DRS	-34.7	-34.7	-43.0	4.83	0	0

					5	5	2			
Kilkenny	80	87	92	DRS	-20.33	-20.13	-20.13	0	5.88	3.5
Laois	100	100	100	CRS	0	0	0	0	0	0
Longford	74	96	77	IRS	-25.95	-25.95	-25.95	41.04	0	0
Louth	60	80	75	IRS	-39.70	39.84	-69.12	14.14	0	0
Meath	78	81	96	DRS	-21.52	-21.73	-52.07	33.99	0	0
Offaly	100	100	100	CRS	0.29	0	-33.27	6.30	0	0
Westmeath	100	100	100	CRS	0	0	0	0.81	0	0
Wexford	70	78	90	DRS	-29.81	-29.65	-29.65	0.81	0	0
Wicklow	91	99	91	DRS	-8.93	-9.11	-8.93	0	13	20.3

Average	**83**	**91**	**91**						**0**	**0**

Total Technical Efficiency (TTE); Pure Technical Efficiency (PTE); Scale Efficiency (TTE/PTE); (RTS) Returns to Scale; X1: Labour; X2:Distribution Length; X3: Transformer Capacity; X4: Distribution Losses; Y1: Energy Consumed; Y2: No of Customers; Y3: Service Area

The average overall efficiency score of all the EDCs is 83%, with 14 EDCs scoring below this average value. This implies that the resource utilization of electricity distribution counties is suboptimal with considerable room for improvement. In order to identify, establish targets and indicate the improvement directions necessary for inefficient EDCs a slack analysis is employed to establish if additional specific output amounts or a decrease in specific input amounts leads to improvements in efficiency ratings. The input slack values represented in Table 6 highlights the necessary reductions of the corresponding input factors to become technically efficient generating units. It can be observed that slacks for efficient plants with an efficiency score of 100% are zero (Dublin). The potential for improvement of inefficient EDCs is also presented in Table 6. (X1, X2, X3, Y2, Y3, Y4) show the potential improvements that are attainable by inefficient EDCs, if inputs and outputs are adapted accordingly. For example, the inefficient Sligo EDC can decrease employees (X1) by 5.27%, distribution length (X2) by 4.92%, transformer capacity (X3) by 4.92% and allow for an increase in energy consumption (Y1) of 19.26%. This means Sligo EDC is over utilizing its inputs at current levels and can be as efficient as its peer group. However, the differences between efficient and inefficient EDCs in terms of distributions losses are not significant. It is clear from the analysis that inefficient EDCs are predominantly associated with medium and large sized service areas. The 5 efficient EDCs are all small sized service areas meaning that these small EDCs are more efficient at integrating their resources. The majority of EDCs present decreasing returns to scale characteristics.

Technical and Scale Efficiency Analysis

The BCC model was adopted to establish technical and scale efficiency of the electricity distribution counties studied. These results indicate the sources of inefficiency amongst the EDCs. When interpreting the BCC scores or pure technical efficiency, the number of efficient EDC rises to 9 with the average pure technical efficiency (PTE) of all the EDCs 91%. EDCs that have a scale efficiency score less than one are scale inefficient. A scale inefficient EDC that exceeds the most productive scale size (MPSS) will present decreasing returns to scale. Alternatively, a scale inefficient EDC that is smaller than the most productive scale size will present increasing returns to scale. MPSS is the optimal operational performance of plants. The EDCs Westmeath, Offaly, Laois, Dublin, Letrim operate on both the CCR and BCC efficiency frontier displaying 100% efficiency, exhibiting constant returns to scale characteristics, and hence are Pareto-Koopmans efficient. Mayo, Galway, Cork, and Carlow, exhibit 100% BCC efficiency but a lower score in CCR, hence are operating locally efficiently but not overall efficiently due to the scale size. They first three EDCs are scale inefficient and should decrease the operation scales to improve overall efficiency as they present decreasing returns to scale with the exception of Carlow. Carlow should increase operational scales. Donegal, Monaghan, Clare, Longford, Louth, and Wicklow all have pure technical efficiency (PTE) scores greater than their corresponding scale efficiency scores. The EDCs of Monaghan, Longford and Louth should increase their operation scales as they exhibit increasing returns to scale to improve overall efficiency. Clare and Wicklow display decreasing returns to scale indicating these EDCs have considerable scope for improvements in their overall efficiency by resizing (decreasing) there scales of operation to the optimal scale MPSS. The remaining nine EDCs all display overall and local technical inefficiency, with a relatively high scale efficiency score. These EDCs could improve their technical efficiency by altering their resource allocation and utilization which would increase their overall efficiency score. Individual efficiency results suggest that the EDCs operating at the relatively more developed eastern part of Ireland have noticeably higher average relative efficiency scores, with performance of EDCs deteriorating towards rural and the western parts of Ireland. This would be due to increased population in Dublin's surrounding EDCs with 40% of Ireland's population residing in the East region (CSO, 2011), resulting in a more densely populated distribution network.

Comparison and Discussion of Models

The six adopted models employ constant returns to scale technologies to establish total technical efficiency (TTE) for each of EDCs under analysis. The numerical efficiency scores attained for the models are given in Table 7. The main study is the comprehensive model against which all other models are compared. Efficiency of each EDC is scored out of 100. The average efficiency of all the models are given. The spearman correlation coefficients are calculated to establish and assess the impact of omitting/including certain variables on the results obtained from the comprehensive model. A spearman correlation coefficient of 100% illustrates the dropped variable(s) have no significant effect on the results obtained from the comprehensive model. The adoption of model 2 reflects the basic structural model for efficiency analysis of electricity distribution utilities extensively used in the literature. The low correlation coefficient of 39% in relation to model 1 suggests omitting (I) distribution losses and (O) service area has a significant effect on the results. This trend of a very low correlation coefficient (35%) is also seen when comparing model 4 with model 1. This implies that establishing two DMU groups reflecting Rural Distribution Counties (RDCs) and Urban Distribution Counties (UDCs) has a significant effect on efficiency scores obtained. However, dropping the variable transformer capacity and including service area in the analysis has considerably less effect on the results, represented by the correlation coefficient of 87%. Comparing the spearman correlation coefficient results obtained for models 5 and 6, it can be seen that the inclusion of industrial output is statistically more significant (0.74) than the inclusion of the environmental variable customer density (0.78).

Table 7 Efficiency scores of all models adopted

EDC	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Donegal	91	64	91	95	91	91
Cavan	63	63	61	69	71	63
Monaghan	71	70	55	72	84	71
Letrim	100	58	100	100	100	100
Sligo	95	84	92	100	95	95
Roscommon	86	40	86	86	88	86
Mayo	98	67	91	98	100	98
Galway	82	51	82	82*	83	82
Clare	93	43	93	94	94	93

Limerick	72	54	72	72*	100	72
Tipperary	74	64	72	78	82	74
Kerry	83	57	83	86	83	83
Cork	70	60	69	70*	100	70
Waterford	89	71	88	89*	96	93
Carlow	73	58	73	89	73	100
Dublin	100	100	100	100*	100	100
Kildare	65	47	65	100	72	67
Kilkenny	80	80	64	80	80	80
Laois	100	100	99	100	100	100
Longford	74	69	67	82	77	83
Louth	60	31	60	100	70	96
Meath	78	44	78	100	78	78
Offaly	100	55	100	100	100	100
Westmeath	100	100	72	100	100	100
Wexford	70	70	62	86	70	70
Wicklow	91	91	78	100	97	91
Mean efficiency Score	**83**	**65**	**79**	**91**	**88**	**86**
SCC with Model 1	-	.39	.87	.35	.74	.78
Minimum efficiency	60	31	55	68	70	63

Score						
Number of efficient EDCs	4	3	3	10	8	6

*Denotes UDCs Urban Distribution Counties; EDCs Electricity Distribution Counties

SCC – Spearman Correlation Coefficients

The inclusion of environmental and categorical variables to account for differences across EDCs has significant effects on efficiency scores. The descriptive statistics for the comprehensive model accounting for EDCs that contain an urban center (City) are presented in Table 8. The comprehensive model was adopted as the full sample of variables was sought for analysis. The total comprehensive efficiency scores are given in Table 7 (model 1). The impact of including environmental categorical variable in model 4 greatly influences the efficiency scores RDCs. Comparing with model 1 average efficiency score increases from 83 -91% with the number of efficient EDCs rising from 5 to 8. When observing all 26 EDCs scale efficiency TTE is relatively low at 83% with scale efficiency being quite high at 91%. The UDC mean scale efficiency is quite close to this at 89% with RDCs scoring a little higher at 94%. When two DMU groups are formed relating to rural and urban electricity distribution centers, it is the former than out performs the latter in terms of total, pure technical and scale efficiency. Similarly the inclusion of a non-discretionary environmental variable in model five increases efficiency for all EDCs with UDCs greatly influenced (Cork, Limerick, Waterford and Galway). Comparing with model 5 with model 1 in terms of average efficiency score, an increases from 83 -88% with the number of efficient EDCs rising from 4 to 10. This is intuitively what one would expect with UDCs producing greater industrial output than RDCs. All EDCs see an increase in efficiency. Non-discretionary models employing the traditional environmental variables inverse density, customer density and customer dispersion were pursued. The model incorporating the customer density variable was most significant. A direct comparison can therefore be made with our constructed diagnostic model employing non-discretionary industrial output (model 5) in place of the traditional environmental variable customer density (model 6). In terms of average overall efficiency model 5 returns a higher efficiency of 88% as opposed to model 6 with 86%. Also the number of efficient EDCs in model 5 is 8, this falls to 5 when observing model 6 in Table 7. All EDCs obtain a higher efficiency score in diagnostic model 5 when compared with the environmental model 6. The diagnostic parameter industrial output has more explanatory power when attempting to account for differing electricity distribution characteristics across EDCs when compared with traditional environmental variables that have been extensively adopted in the DEA literature.

Table 8 Descriptive statistics of EDCs divided into categories of RDCs and UDCs

Model 1	**Number of EDCs**	**Mean Efficiency Score**	**Standard Deviation**	**Minimum Value**	**Maximum Value**	**No of Efficient EDCs**
All EDCs						
TTE	26	0.83	0.126	0.60	100	4
PTE	26	0.91	0.106	0.65	100	9
SE	26	0.91			100	6

RDCs						
TTE	21	0.91	0.099	0.69	100	9
PTE	21	0.96	0.068	0.71	100	14
SE	21	0.94			100	9
UDCs						
TTE	5	0.83	0.126	0.72	100	1
PTE	5	0.93	0.175	0.76	100	3
SE	5	0.88			100	1

SE = TTE/PTE; EDC = Electricity Distribution Counties; RDCs – Rural Distribution Counties; UDCs – Urban Distribution Counties.

Efficiency Improvement through Reorganization of EDCs

In this study, we investigated possible reorganisation alternatives to reduce the number of EDCs to improve resource utilization and promote efficiency are investigated. Reorganisation and operational mergers are feasible methods to increase efficiency. Thus, the objective of EDC reorganisation was focused on improving overall efficiency. Based on geographical convenience, a restructuring and amalgamation of the current 26 EDCs within ESB Networks distribution framework has been hypothesized. Ireland with its relatively small size, sparse population and installed capacity would benefit from the aggregation of the 26 EDCs to 11 more efficient and manageable Electricity distribution Zones (EDZ’s). This would also greatly reduce duplication of services between EDCs. Due to geographical limitations, only adjacent EDCs are combined to form EDZs. To examine the reorganization alternatives, the CCR and BCC models were applied to establish total technical efficiency (TTE) and pure technical efficiency (PTE) along with scale efficiency (SE). Due to the reduction in number of DMUs employed comparisons are only made with the original basic and quality models (2 and 3) These models have been extensively adopted in the literature. The results of the restructuring are displayed in Table 9. For example EDCs Offaly, Laois and Kilkenny can combine to form the Central Electricity Distribution Zone.

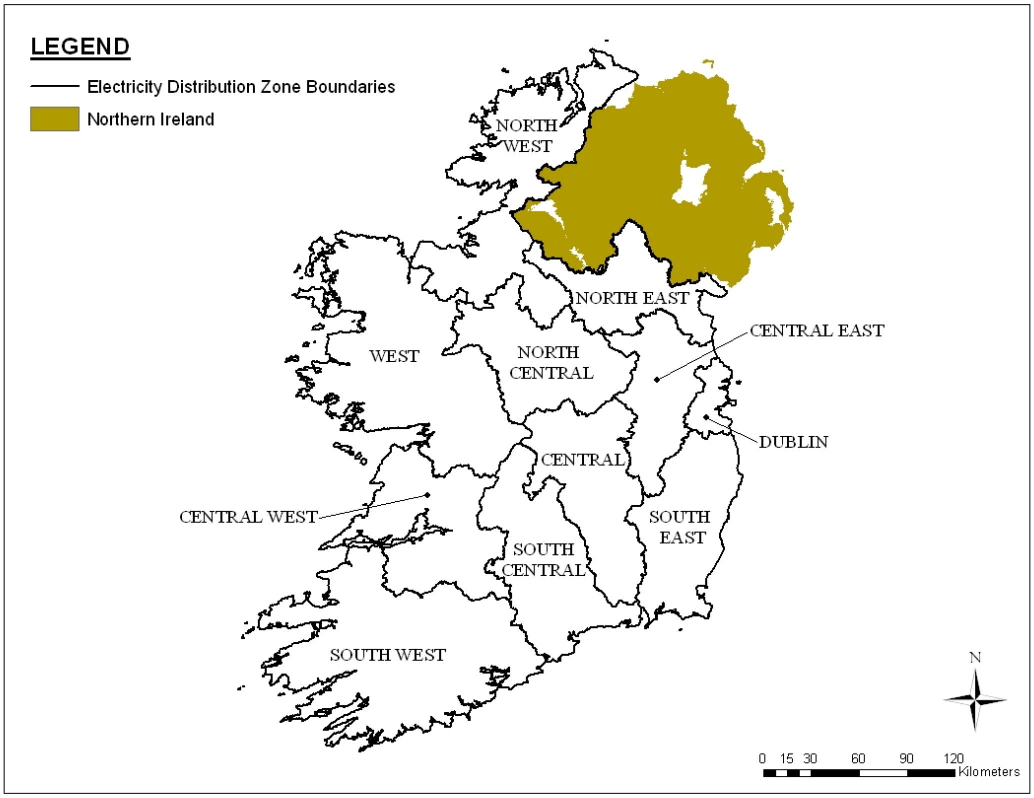

Fig. 2 Electricity Distribution Zones (EDZs)

In terms of the basic model both cases, the efficiency results obtained are significantly higher after TTE increasing 15% from 65-80% whilst PTE efficiency increased 14% from 79% to 93% after reorganization of EDCs. A similar trend is observed when comparing the quality model before with both the TTE and PTE score higher after restructuring. TTE increases by 6% to 85% PTE and increases by 10% to 95%. When observing all eight models under constant and variables returns to scale, comparing pre and post electricity distribution restructuring, little variation is shown amongst the number of efficient DMUs but efficiency is gained when employing the Electricity Distribution Zones concept for distribution.

Table 9 Reorganization of EDCs into EDZs to improve efficiency

EDC Model 2	**CCR-I**	**BCC-I**	**Scale Efficiency**
Donegal	64	72	88
Letrim	58	100	58
Sligo	84	91	92
North West Zone	**94**	**98**	**96**
Mayo	67	98	68
Galway	51	57	89
West Zone	**76**	**82**	**93**
Clare	43	49	88
Limerick	54	55	98
Central West Zone	**57**	**86**	**66**
Kerry	57	63	90

Cork	60	75	80
South West Zone	**74**	**80**	**93**
Roscommon	40	54	74
Longford	69	96	72
Westmeath	100	100	100
North Central Zone	**91**	**99**	**92**
Offaly	55	76	72
Laois	100	100	100
Kilkenny	80	85	94
Central Zone	**100**	**100**	**100**
Tipperary	64	83	77
Waterford	71	80	89
South Central Zone	**92**	**94**	**98**
Cavan	63	65	97
Monaghan	70	96	73
Louth	31	80	39
North East Zone	**50**	**86**	**58**
Kildare	47	56	84
Meath	44	53	83

Central East Zone	**47**	**95**	**49**
Dublin East Zone	**100**	**100**	**100**
Carlow	58	100	58
Wexford	70	76	92
Wicklow	91	97	94
South East Zone	**100**	**100**	**100**
	CCR-I	**BCC-I**	
Basic Model 2	65 (3)	79 (5)	
Reorganised Model 2	80 (3)	93 (3)	
Quality Model 3	79 (3)	85 (7)	
Reorganised Model 3	85 (2)	95 (5)	

Note Figures in the parenthesis represent efficient DMUs

7. Conclusions

This study has extended the literature on efficiency analysis to the electricity distribution sector in the Republic of Ireland. The employment of the Irish electricity distribution system and Electricity Distribution Counties (EDC) as the main research focus has never been done. The paper provides a DEA framework to measure technical efficiency; to establish if empirical efficiency gains were possible, and to investigate the reorganisation of the electricity distribution network for efficiency gains. The paper has explored the efficiency and benchmarks of the EDCs from a comprehensive viewpoint with the employment of five differing models to capture the characteristics of EDCs. Analysis, discussion and presentation of key findings comparing all five models are presented. External factors that are not controllable by EDCs can inhibit efficiency. This was accounted for by adopting a categorical variable to account for urban/rural environments and a diagnostic parameter to account for differing electricity distribution characteristics across EDCs, comparisons were made with employing traditional environmental variables. The adoption of the diagnostic parameter proves to be a superior variable. The proposed reorganization alternative of employed Electricity Distribution Zones (EDZ) achieved higher efficiency scores of up 10%. The results of this paper can assist ESB networks to improve the operational management of EDCs. Also, this empirical analysis can provide useful information to the policy makers responsible for electricity distribution regulation under changing market regimes. The DEA benchmark approach employed here offers an alternative form of electricity distribution regulation open to the Commission for Energy Regulation (CER) in Ireland as opposed to the status quo of OPEX and CAPEX regulation. This alternative approach can be adopted by other countries with similar electricity distribution environments.

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