INCORPORATING QUALITY OF SERVICE IN A BENCHMARKING MODEL: AN APPLICATION TO FRENCH ELECTRICITY DISTRIBUTION OPERATORS

by

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ABSTRACT

In this paper we use annual data on 92 French electricity distribution units (2003-2005) to estimate a benchmarking model that includes a quality of service indicator (number of interruptions). Our methodology involves the estimation of input distance functions using stochastic frontier analysis (SFA) and data envelopment analysis (DEA) techniques. The empirical results indicate that the inclusion of the quality variable has no significant effect upon mean technical efficiency scores, and the mean shadow price of one interruption is approximately ten Euros.

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1. INTRODUCTION

The electricity supply industries in many countries have undergone profound changes in recent decades.[1] In a number of these countries, market mechanisms have been introduced in the generation and supply activities.

Over Europe, member states moves on the path of liberalisation at different paces. To illustrate these differences one may mention as an example France and Germany. In Germany the market has been entirely open to all customers independently of their consumption level since 1998. In France, the liberalisation process started in 2000. It was undertaken progressively step by step. In the first stage the liberalisation process only concerned the electro-intensive customers. In the current final stage, which started on July 2007, the whole French market is fully opened to competition.

In this liberalisation process, the network activities (the so-called wires businesses) given their natural monopoly specificity require a regulation framework, which is either defined by the industry itself (self regulation) or by an independent regulation authority. The German experience illustrated how self-regulation appeared to be inappropriate to guarantee a same level playing field among the market players of the German electricity markets.

Independent regulatory authorities, which were set up in the different European states, are thus required to monitor the wires businesses operated by grid operators (Distribution System Operator and). They ensure that all market players have a fair access to an essential facility at a fair access charge.

The role of these regulation authorities is thus to prevent a regulated grid operator from the realisation of any economic profit. To ensure this task, he usually sets a tariff, the access charge, which allows the grid operator to fully recover their total costs.

Meanwhile this regulation scheme does not provide grid operators incentives to achieve cost efficiency as they may overinvest in capital, an effect pointed out by Averch-Johnson (1962). To avoid the emergence of this effect, regulators can rely on a specific regulation scheme, called incentive regulation. In such scheme, the regulator defines productivity objectives, which should be achieved by the grid operator. Such efforts are costly for DSO, they will undertake them whether they are rewarded for them.

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[1] For example, see Newberry (2000).

Given that a regulator generally has some uncertainty regarding the efficient level of a DSO's costs, the grid operator can be rewarded for the effort beyond the efficient level. Benchmarking thus may appear as a useful tool for a regulator to use in assessing the efficiency and the performance of a DSO.[2] A robust benchmarking model can help the industry regulators to determine the relative efficiency of different DSOs and to set their reasonable targets in term of cost efficiency. But these methods have a caveat, since they can create incentives for cost reductions which may have an impact on the quality of service. A challenge for the regulatory body is to find a suitable method to ensure that cost reductions do not have an adverse effect on the quality of electricity distribution.

For that purpose, regulators normally rely on tariff and quality incentive schemes.[3] Usually these two schemes are separated. The tariff incentive scheme, generally involving a revenue-cap or a price-cap regulation, often makes use of a benchmarking model that seeks to identify the efficient level of costs for each operator. The quality incentive scheme on the other hand generally involves a reward/penalty mechanism that is based on pre-specified performance levels in terms of acceptable outages (frequency and/or duration).[4]

An alternative approach could be to include the quality aspect into the efficiency benchmarking. By doing so, the efficiency requirement also includes incentives for quality improvements. The purpose of this study is thus to investigate the feasibility of combining both incentive schemes into one. In particular, we investigate alternative efficiency measurement models that also incorporate quality measures that could then give a good idea of the real efficiency of a distribution company, that can take into account its structural constraints and public service obligations.

Up till now, most widely used benchmarking analyses in electricity distribution have involved models that incorporate standard output characteristics, such as energy supplied (in MWh), number of customers and network size (e.g., service area or network length). For example, see the literature review in London Economics (1999) and Jamasb and Pollitt (2001).

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[2] See Coelli *et al* (2003) for further discussion.

[3] See Giannakis *et al* (2005) and Fumagalli *et al* (2007) for more on this.

[4] See Lawrence and Diewert (2006, p215) for an interesting discussion of why they were unable to include a quality variable in their electricity distribution benchmarking model which was used to set regulated access prices in New Zealand. Their benchmarking model involved the use of total factor productivity indices, which do not incorporate "bad outputs" easily.

However, very few studies have included quality of service measures in these models. Two recent exceptions are the studies by Giannakis, Jamasb and Pollitt (2005) and Growitsch, Jamasb and Pollitt (2005).

Giannakis et al (2005) use data envelopment analysis (DEA) methods to measure technical efficiency (TE) and total factor productivity growth (TFP) in 14 UK distribution authorities over the 1991/92 to 1998/99 period. The DEA method is used to estimate a non-parametric input distance function that involves three output variables (energy supplied, customers and network length). Four models involving different input sets are considered: (i) operating expenditure (OPEX); (ii) total expenditure (TOTEX); (iii) number of interruptions (NINT) and total interruptions (TINT); and (iv) TOTEX, NINT and TINT. They find that the TE scores of the various models are positively (but not perfectly) correlated, and that the TE scores rise when the NINT and TINT quality variables are added to the TOTEX model (a result that is to be mathematically expected when variables are added to a DEA model).[5] They also find that TFP growth measures reduces by 40% when the quality variables are added.

Growitsch et al (2005) use stochastic frontier analysis (SFA) methods to estimate an input distance function using data on 505 electricity distribution utilities from eight European countries in the 2002 financial year. Their models contain two output variables (energy supplied and customers) and either one input variable (TOTEX) or two input variables (TOTEX and TINT). They also use the Battese and Coelli (1995) method to investigate the effects of customer density (customers per network km) and country (using dummy variables) upon technical efficiency scores. They find that the inclusion of the quality variable reduces TE for all but the large firms, plus they find that the TE scores from the two models are significantly negatively correlated, both findings being in contrast to those of Giannakis et al (2005).

The above studies are to be commended for introducing quality variables into these benchmarking models. However, these studies contain some shortcomings. First, they both make use of TOTEX measures which contain capital expenditure (CAPEX) measures which

[5] This is also seen in a DEA study by Korhonen and Syrjänen (2003) of Finnish electricity distribution operators, where the inclusion of a TINT variable into the DEA model led to increases in technical efficiency for a number of firms. For example, see their Figure 3. However, note that these results need to be treated with caution because their DEA model did not include a capital measure, which could lead to substantial biases.

need not reflect the actual amount of capital services consumed in a particular year. Second, the UK study suffers from small sample size problems while the inter-country study suffers from difficulties associated with deflating monetary values of TOTEX in order to obtain comparable measures of implicit input usage in each country.

In the current study we aim to address these problems by making use of a detailed database on the activities of 92 electricity distribution units operated by EDF Réseau Distribution in France in the 2003–2005 financial years.

In France, most electricity distribution grids which are owned by municipalities, individually or grouped in communities. Municipalities are in charge of the public service of electricity distribution, which they delegate to a third party DSO within the framework of a concession. The concession contracts between parties follow a similar model. The public service requirements are, indeed, the same all over the country.

The concession contracts define the rights and obligations of the distributor regarding quality of supply, customers' connections and environmental conditions. These contracts state that the distributor is remunerated by the tariff applied to final users, which is supposed to cover costs and investments. This tariff is the same for all the concessions (one single pricing for all the customers in France) and for all DSOs. The rates for the use of public electricity grids, including transmission and distribution networks, are set by the French Regulator, the CRE (Commission de Régulation de l'Energie).

In this study, all distribution units are operated by EDF Réseau Distribution, while the units in the previous studies were regarded as individual operators. With these data we thus avoid the small sample size problem; we avoid the international comparability problem; and we also have access to comprehensive and comparable data on the replacement value of capital items, so we can avoid the need to use CAPEX to measure capital input services.

In addition to these advantages, we also utilise both DEA and SFA methods in this paper to check for consistency across methodologies. Furthermore, as well as measuring the effect of quality upon TE scores, we also make use of the methods described in Grosskopf et al (1995) and Coelli and Rao (1998) to derive measures of the shadow price of quality from the curvature of the estimated distance functions. This information could be quite valuable in allowing one to assess the degree to which rewards for quality outcomes could influence the services provided.

The remainder of this paper is divided in sections. In Section 2 we present a description of the DEA and SFA methodologies used. In Section 3 we describe the data, before presenting and discussing the empirical results in Section 4. The paper ends with some brief concluding comments in Section 5.

2. METHODOLOGY

The methods used in this paper are similar to those used in the Growitsch et al (2005) and Giannakis et al (2005) studies. We model the production process using a multi-input, multi-output input distance function and introduce the quality variable as an input variable. The logic associated with including the quality variable as an input variable is that the operators can substitute between regular inputs (labour, capital etc.) and the inconvenience faced by the customers (interruptions). The rational operator will look at the "price of interruptions" (e.g., the penalty imposed by the regulator) and compare it with the price of other inputs (e.g., labour) before deciding upon the optimal (cost minimising) mix of inputs to use.

If the production technology (frontier) is known (which is rarely the case) we can measure the distance that each data point (firm) lies below the frontier by calculating the amount by which the input vector (**x**) can be proportionally reduced while holding the output vector (**y**) constant. That is, for each data point (**x**,**y**) we seek to find the smallest possible value of the scalar θ such that (θ**x**,**y**) remains within the feasible production set bounded by the frontier. This is illustrated (for the case of a 2-input technology) in Figure 1, where the distance that firm A is inside the frontier is equal to θ=0*B*/0*A*. This distance (i.e., technical efficiency score) equals approximately 0.7 in this diagram, suggesting that the firm could reduce input usage by 30% and still produce the same output vector.

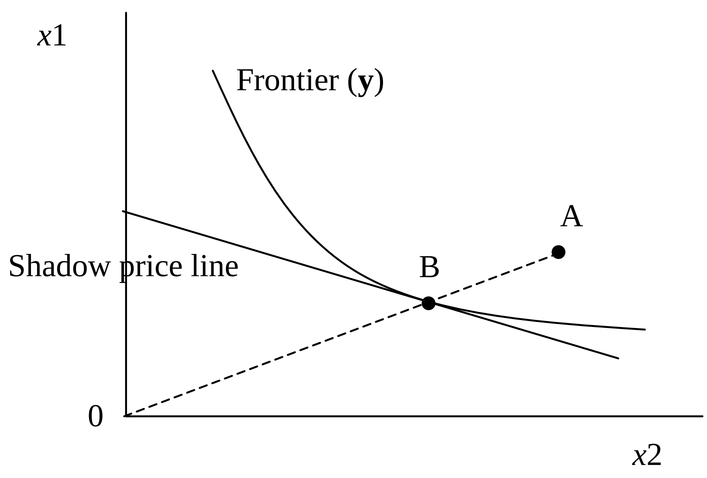

Figure 1: Input oriented technical efficiency

In reality, the production frontier is rarely known. Instead it is estimated using sample data on a number of firms. This generally involves fitting an empirical frontier that aims to minimise these distances so that the frontier is a "tight-fit" to the data. In this paper we use both SFA and DEA methods to estimate an input distance function.

The input distance function may be defined on the input set, $L(\mathbf{y})$, as:

$$D_I(\mathbf{x},\mathbf{y}) = \max\left\{\rho : (\mathbf{x}/\rho) \in L(\mathbf{y})\right\}, \tag{1}$$

where $\rho = 1/\theta$ and the input set $L(\mathbf{y})$ represents the set of all input vectors, $\mathbf{x} \in R_+^K$, which can produce the output vector, $\mathbf{y} \in R_+^M$. That is,

$$L(\mathbf{y}) = \left\{\mathbf{x} \in R_+^K : \mathbf{x} \text{ can produce } \mathbf{y}\right\}. \tag{2}$$

$D_I(\mathbf{x},\mathbf{y})$ is non-decreasing, positively linearly homogeneous and concave in **x**, and increasing in **y**. The distance function will take a value which is greater than or equal to one if the input vector, **x**, is an element of the feasible input set, $L(\mathbf{y})$. That is, $D_I(\mathbf{x},\mathbf{y}) \geq 1$ if $\mathbf{x} \in L(\mathbf{y})$. Furthermore, the distance function will take a value of unity if **x** is located on the inner boundary of the input set.

Stochastic frontier analysis (SFA)

Following Coelli *et al* (2003), a translog input distance function for the case of *M* outputs and *K* inputs is specified as

$$\begin{aligned} \ln D_{Ii} = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} \\ & + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi}, \quad i = 1,2,\ldots,N \end{aligned} \tag{3}$$

where *i* denotes the *i*-th firm in the sample of *N* firms.[6] Note that to obtain the frontier surface (i.e., the transformation function) one would set D_i=1, which implies the left hand side of equation (3) is equal to zero.

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[6] Note that in our application we have annual data on 92 units over a three year period. Hence we have 276 observations. Given the short time period we assume that there has been no technological progress over this

Imposing homogeneity of degree +1 in inputs and rearranging we obtain

$$\ln\left(1/x_{Ki}\right) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K-1} \beta_k \ln x_{ki}^{*}$$
$$+ \frac{1}{2}\sum_{k=1}^{K-1}\sum_{l=1}^{K-1} \beta_{kl} \ln x_{ki}^{*} \ln x_{li}^{*} + \sum_{k=1}^{K-1}\sum_{m=1}^{M} \delta_{km} \ln x_{ki}^{*} \ln y_{mi} - \ln D_i, \quad i = 1, 2, ..., N \qquad (4)$$

where $x_{ki}^{*} = x_{ki} / x_{Ki}$.

The restrictions required for homogeneity of degree +1 in inputs are

$$\sum_{k=1}^{K} \beta_k = 1$$

and

$$\sum_{l=1}^{K} \beta_{kl} = 0, \quad k=1,2,...,K, \quad \text{and} \quad \sum_{k=1}^{K} \beta_{km} = 0, \quad m=1,2,...,M,$$

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period and hence pool the data as if it was a single year of data on 276 firms when estimating the production frontiers.

and those required for symmetry are

$$\alpha_{mn} = \alpha_{nm}, \quad m,n=1,2,...,M, \quad \text{and} \quad \beta_{kl} = \beta_{kl}, \quad k,\text{l}=1,2,...,K.$$

To estimate this model using SFA methods we replace the distance term with an error term that has two *i.i.d.* components, $\ln D_i = v_i - u_i$, where v_i ~ $|N(0,\sigma_v^2)|$ is a symmetric error to account for data noise and the u_i ~ $|N(\mu,\sigma_u^2)|$ is a one-sided error to account for technical inefficiency. The technical efficiency score for the *i*-th firm is predicted using the conditional expectation $E[\exp(-u_i \mid v_i - u_i)]$, which takes a value between 0 and 1. The model is estimated using maximum likelihood ML) methods. Note that prior to estimation the variance parameters, σ_v^2 and σ_u^2 are re-parameterised as $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$ for computational convenience.

Data Envelopment Analysis (DEA)

We also estimate an input distance function using DEA methods. This is a non-parametric method where the frontier surface is a sequence of interconnected hyper-planes that are constructed using linear programming methods. The technical efficiency scores are produced as a by-product of the frontier construction process.

We begin by defining the additional notation that **X** represents the $K \times N$ matrix of inputs, which is constructed by placing the input vectors, $\mathbf{x}_i$, of all N firms side by side, and **Y** denotes the $M \times N$ output matrix which is formed in an analogous manner.

The input-orientated variable returns to scale (VRS) DEA frontier is defined by the solution to N linear programs of the form:

$$\begin{aligned}
&\max_{\rho,\lambda} \rho, \\
&\text{st} \quad -\mathbf{y}_i + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\
&\qquad \mathbf{x}_i/\rho - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0}, \\
&\qquad \mathbf{N1}'\boldsymbol{\lambda}=1 \\
&\boldsymbol{\lambda} \geq \mathbf{0},
\end{aligned} \tag{8}$$

where ρ is the input distance measure defined earlier. We note that $1 \leq \rho \leq \infty$ and that $1/\rho$ is the proportional reduction in inputs that could be achieved by the *i*-th firm, with output quantities held constant. For further details on DEA, SFA and distance functions in general, see Coelli *et al* (2005).

3. MEASUREMENT OF VARIABLES

The selection and measurement of input and output variables is a key aspect of any efficiency analysis study. In this paper we have drawn upon our knowledge of the key cost drivers in the French electricity distribution industry, along with reviewing the experiences gained in previous analyses. For example, see those studies surveyed in London Economics (1999) and Jamasb and Pollitt (2001), and more recent studies, such as Lawrence and Diewert (2006) and Edvardsen et al (2006).

Three output variables are used in the present study: energy supplied, number of customers and network length or, alternatively, the service area. The amount of energy supplied in gigawatt hours (GWH) is generally the first output variable thought of, since the aim of a distribution company is to "supply electricity to customers". Although a distribution network operator cannot normally determine the amount of electricity distributed, it has to ensure that all its network assets have the capacity to deliver this energy to its customers. Hence, the total amount of energy supplied may be viewed as a proxy for the load capacity of the network. The measure used in this study is gross electricity distributed (which includes losses).

The number of customers (CUST) is also used as an output variable in our model because we believe that this variable is needed to ensure that the model does not unfairly discriminate against those operators which sell smaller amounts of energy per customer. Furthermore, a large part of distribution activities (relating to metering services, customer connections, customer calls, billing, etc.) are directly correlated to the number of customers. Note that our measure only includes Low Voltage (LV) customers, since industrial customers who are connected to the Medium Voltage (MV) network are rather small in number.

Finally, network length (NETL) in kilometres or, alternatively, the service area in squared kilometres (KM2) is used as an additional output variable in our model to accommodate differences in customer densities across operators. A lot of network operations, such as routine maintenance, overhaul, vegetation management for overhead lines, etc. are closely linked to the length of MV and LV lines or, indirectly, to the the size of the area served. Moreover, the reliability of a distribution network and therefore the level of quality of supply is often affected by the length of feeders that is, in other words, by customers' density. In big cities, where the feeders are mostly short and underground, the number of outages should be lower than in less dense areas which tend to have a high proportion of overhead lines. As a consequence, the costs of repairs are generally not the same in urban versus rural areas.

The net effect of using these three output variables in our model is to ensure that the key aspects of output heterogeneity are captured, so that when we conduct benchmarking comparisons using technical efficiency (TE) measures, we are conditioning on these factors and hence comparing like with like. That is, not comparing distribution units like Lille with the Southern Alps, and so on. Nevertheless, we are aware that with three output variables, we are unable to control for all environmental differences that could influence costs, such as influence of forests and mountainous terrain, ages of the assets, accessibility of lines or substations, climatic factors, etc.

The inputs used in electricity distribution are many and varied. In terms of capital inputs there are underground and overhead lines of various voltage levels, transformers, vehicles, computers, and so on. Plus we have various types of labour – technicians, engineers, managers, etc. – plus a variety of other materials and services. One could perhaps define dozens of input variables, but degrees of freedom limitations in the production model prevent us from doing that. Instead we have chosen to define only two input variables – capital inputs (CAPITAL) and non capital inputs (OPEX).

Capital is measured using gross (not depreciated) replacement value. We have chosen gross in preference to net because we wish to avoid the situation where an operator that has conducted a lot of recent investment is labelled as inefficient because their net capital stock is high relative to others. In using this measure we implicitly make two assumptions. First we assume that asset age does not significantly affect service potential. Second we assume that all operators have assets with similar life spans and hence that annual service potential is proportional to the stock. These assumptions are arguably quite reasonable in the current study, since all the data come from a single distribution operator (EDF Réseau Distribution) who defines and manages very similar policies for investment, operations and network asset development across the various local distribution units.

In terms of non-capital inputs, we use network operating expenses net of depreciation and interest as our aggregate measure of these items. These are the direct operational costs of local distribution units, excluding centralized network service support and overhead costs.

These operational costs relate to day-to-day operations, such as:

- operating, developing and maintaining distribution network assets: looking after substations and overhead lines, fault repairs, remote control and dispatching, and so on;
- running connections services;
- providing meter services and any other customer interventions;
- relations with local authorities and customers; etc.

We could have chosen to split this OPEX grouping into labour and non-labour groups, but given that labour expense dominates this category and that outsourcing is blurring the boundaries between these two categories, we decided to use a single variable.[7]

Finally, quality is measured as the total number of interruptions (NINT) – excluding short interruptions of three minutes or less. We could have alternatively considered using a total minutes of interruptions (MINT) measure, but we felt that this latter measure would be more influenced by random geographical factors that are not under the control of managers, relative to the NINT measure. The total number of interruptions NINT has been calculated as follows:

$$\text{NINT} = \text{SAIFI} \times \text{Total number of customers}$$

According to the international standards relative to quality of supply, SAIFI (System Average Interruption Frequency) is the average number of sustained interruptions (>3 min) experienced per customer served per year.

$$\text{SAIFI} = \frac{\text{Total number of customer interruptions}}{\text{Total number of customers served}}$$

Therefore, NINT represents the total number of outages. It includes unplanned interruptions, even those for which the distribution company is not responsible (transmission network, third-part, …), and also planned interruptions (e.g., to accommodate extensions, upgrades, etc.). Exceptional events have been excluded in order not to disadvantage distribution units which experienced major climatic events (big storms, floods, etc.) in the study period.

[7] CAPITAL and OPEX variables are expressed in 2005 prices using a gross industrial commodities price deflator.

Table 1: Descriptive Statistics

Variable		mean	st. dev.	min.	max.
CUST	y_1	324857	134162	109435	762905
NETL	y_2	13359	6165	4060	32743
KM2	y_2	5532	3125	129	13871
GWH	y_3	3557	1477	1001	7976
OPEX	x_1	22194	8222	10575	57591
CAPITAL	x_2	626924	215874	250001	1212792
NINT	x_3	390420	249524	49901	1927519

Note: OPEX and CAPITAL in 1,000 €. Paris excluded; NINT in number of customers interrupted; KM2 in Km^2.

4. EMPIRICAL RESULTS

In this section we present the results of the estimation of alternative models, input distance functions including or not quality, performed using SFA and DEA. Our objective is three-fold. First, to investigate the statistical sensibility of results to the inclusion of quality in SFA estimations. Second, to compare the technical efficiency, SFA and DEA, scores obtained by each operator taking or not quality into account as an alternative way to identify potential trade-offs between quantity and quality improvements. Third, to analyze how electricity distribution operators behave to take into account quality, mainly service interruptions faced by customers, in their cost minimization decisions or, in other word, we estimate the shadow prices operators associate to quality in their operational design.

SFA model estimation

The “base model” output variables are CUST, NETL (or KM2) and GWH (y1, y2, y3) and the input variables are OPEX, CAPITAL and NINT (x1, x2, x3). When we refer to the “without quality” model we refer to a model with all of the above variables, with the exception of the NINT quality variable.

The ML estimates of the SFA “without quality” and “base” models are listed in Table 2. The results for two alternative specifications, with NETL or KM2 as y_2 output, are reported. Each variable has been divided by its sample mean and hence the first order parameters can be interpreted as elasticities at the sample means. All input and output elasticities have the expected signs for average variable values.

In the input side, it is the elasticity with respect to capital (CAP) that dominates, with values close to 0.90, while elasticity with respect to operational expenditures (OPEX) oscillates around 0.10 and that corresponding to quality (NINT) 0.015 and 0.014 under the models with NETW and KM2 as network sizes, respectively.

In the output side, it is the elasticity with respect to the number of customers (CUST) that dominates the elasticity with respect the network size, especially when the size is represented by the service area (KM2), and the elasticity with respect to energy distributed (GWH) that in all cases reach rather small values, closer to 0.05-0.07. Ray scale economies are calculated as the negative of the inverse of the sum of these output elasticities. It varies from 1.049 to 1.099 across models indicating mildly increasing returns to scale at the sample mean.

Two annual dummies were introduced in the model to catch potential inter-temporal shifts at the frontier level. No significant changes are observed during the first year (2003 to 2004), but a negative and significant change is estimated for the second year (2004 to 2005), particularly under the KM2 specification with an annual rate close to – 2.0%. Note also that the γ coefficient is in all cases near 1.0 indicating that the share of the inefficiency term variance in the total composed error variance is near 100%.

Summing up, the results presented in Table 2 illustrate the main features of electricity distribution activity in France over the period 2003 to 2005, as corresponding to the 92 EDF DSO analysed here. Even if the role of quality appears to be rather small, and in some cases associated with statistically insignificant estimators, LLR tests performed on both models indicate that quality matters. Nevertheless, given that the value of LLR test for the model with KM2 gives a higher value, 97.0 (d.f. = 6), than the model with NETW, 20.0 (d.f. = 6), we retain this model results for presentation purposes in the following sections.

Table 2: SFA Estimates

Variables	Network length (NETW)				Area served (KM2)			
	without quality		base		without quality		base	
	Coef.	(t-ratio)	Coef.	(t-ratio)	Coef.	(t-ratio)	Coef.	(t-ratio)
Intercept	0.120	(11.8)	0.118	(11.1)	0.312	(22.1)	0.340	(17.0)
x_1 (OPEX)	0.093	(*)	0.111	(*)	0.072	(*)	0.105	(*)
x_2 (CAP)	0.907	(59.5)	0.874	(53.8)	0.928	(46.3)	0.881	(45.6)
x_3 (NINT)	-	-	0.015	(2.6)	-	-	0.014	(2.1)
x_1x_1	-0.150	(*)	-0.188	(*)	-0.182	(*)	0.150	(*)
x_2x_2	-0.150	(2.6)	-0.063	(1.0)	-0.182	(2.9)	-0.141	(2.1)
x_3x_3	-	-	-0.018	(1.3)	-	-	-0.010	(0.6)
x_1x_2	0.150	(*)	0.116	(*)	0.182	(*)	0.184	(*)
x_1x_3	-	-	0.072	(*)	-	-	0.053	(*)
x_2x_3	-	-	-0.053	(2.5)	-	-	-0.043	(1.4)
y_1 (CUST)	-0.452	(16.5)	-0.463	(15.3)	-0.707	(22.2)	-0.667	(17.3)
y_2 (NETW,KM2)	-0.400	(24.0)	-0.393	(21.9)	-0.192	(16.0)	-0.200	(17.6)
y_3 (GWH)	-0.064	(3.0)	-0.054	(2.3)	-0.054	(1.7)	-0.069	(2.4)
y_1y_1	-0.336	(1.8)	-0.239	(1.2)	0.249	(1.0)	0.153	(0.7)
y_2y_2	0.038	(0.7)	0.062	(1.0)	-0.018	(1.2)	-0.041	(2.8)
y_3y_3	-0.095	(0.6)	0.082	(0.5)	0.403	(2.3)	0.281	(1.7)
y_1y_2	0.180	(3.7)	0.143	(2.5)	0.106	(2.5)	0.034	(0.9)
y_1y_3	0.178	(1.1)	0.035	(0.2)	-0.419	(2.1)	-0.294	(1.6)
y_2y_3	-0.092	(2.2)	-0.082	(1.8)	-0.071	(2.4)	-0.061	(2.7)
x_1y_1	-0.080	(*)	-0.188	(*)	-0.142	(*)	-0.130	(*)
x_1y_2	0.028	(*)	0.049	(*)	-0.020	(*)	0.007	(*)
x_1y_3	0.047	(*)	0.119	(*)	0.088	(*)	0.079	(*)
x_2y_1	0.080	(1.0)	0.237	(2.7)	0.142	(1.5)	0.180	(1.9)
x_2y_2	-0.028	(1.1)	-0.063	(2.3)	0.020	(1.6)	-0.005	(0.4)
x_2y_3	-0.047	(0.6)	-0.177	(2.3)	-0.088	(1.0)	-0.133	(1.5)
x_3y_1	-	-	-0.049	(1.8)	-	-	-0.050	(1.4)
x_3y_2	-	-	0.015	(1.6)	-	-	-0.001	(0.3)
x_3y_3	-	-	0.058	(2.4)	-	-	0.054	(1.8)
d_1 (year 2004)	-0.001	(0.4)	0.004	(1.5)	0.006	(1.8)	0.005	(1.6)
d_2 (year 2005)	0.007	(2.4)	0.016	(4.3)	0.021	(5.2)	0.022	(4.9)
σ	0.016	(2.7)	0.016	(2.6)	0.012	(10.4)	0.022	(8.7)
γ	0.985	(168.4)	0.986	(171.6)	0.976	(416.8)	0.990	(427.6)
μ	0.034	(0.6)	0.043	(0.8)	0.214	(10.1)	0.293	(14.4)
LLF	564.3		574.3		470.3		518.8	

(*) Parameter computed applying homogeneity conditions.

Technical efficiency: DEA vs. SFA

The means and standard deviations of the TE scores from the SFA and DEA models (with and without quality) are listed in Table 3. The SFA and DEA models have quite similar means. Furthermore, the exclusion of the quality variable does not have a significant effect upon mean TE. This is not surprising given the small size of the quality elasticity in the SFA results in Table 2. Actually, the comparison should be done in terms of evolution of ranking between the models with and without quality, and not on a TE scores comparison.

This suggests that the incorporation of quality into a benchmarking model is unlikely to have a substantial effect upon price regulation outcomes. However, our empirical results differ from those reported in Growitsch *et al* (2005) and Giannakis *et al* (2005). Perhaps our results could be in part a consequence of the short period covered by the data and the relative uniformity of quality regimes across these 92 EDF distribution units? In future work we plan to incorporate data from other operators in other countries to test this hypothesis.

Table 3
Technical efficiency scores

		DEA		SFA	
		without quality	base	without quality	base
Descriptive statistics					
mean		0.823	0.829	0.756	0.741
std		0.123	0.125	0.101	0.099
min		0.532	0.532	0.556	0.554
max		1.000	1.000	0.994	0.989
Correlation table					
DEA	without quality	1.000	0.988	0.499	0.510
	base	0.988	1.000	0.502	0.516
SFA	without quality	0.499	0.502	1.000	0.989
	base	0.510	0.516	0.989	1.000

Shadow shares and prices

Nevertheless, we derive interesting conclusions from the study of input shadow prices and input shares obtained from the estimation of the model. Input shadow prices reflect the potential trade-offs between inputs. The slope of the shadow price line in Figure 1 (which is at a tangent to frontier at the point where the firm is operating) reflects these trade-offs.

When a frontier is estimated we can find the slope of this line for each firm. If the price of one regular input is known then the shadow price of the NINT input can be calculated. Some average shadow price estimates for NINT are listed in Table 4, which have been obtained using the OPEX input price (1 Euro). These values are interpreted such that the mean value of 7.6 from the SFA model suggests that the marginal cost of reducing one interruption (on average) would be 7.6 Euros. However, we note that the DEA estimate is 50% larger than this SFA estimate (10.6 Euros) and that the shadow price varies substantially across quintiles, indicating that the marginal cost is higher for those operators which already have low rates of interruptions by customer (SAIFI), as one would expect. This result is confirmed, mainly for the SFA model, when looking to average quality shadow prices by quintiles distinguished by customers' density or by the share of network underground lines, two features that appear to be highly correlated with quality in electricity distribution among French DSO operators.

In Table 4 average shadow shares by quintiles are also reported. They correspond to the SFA partial elasticities of the distance function with respect OPEX, CAP and NINT variables, respectively. It appears that distribution units performing lowest quality levels (Q5) are characterised by higher OPEX and lower CAPITAL shadow shares, while the opposite is verified for operators reaching higher quality standards (Q1). Nevertheless, these results do not allow us to conclude any correlation between the investment policy of a utility and the level of quality since they are inherently linked to the customer density (urban vs. rural) in the supplied area as it can be observed at the bottom of the same table.

5. CONCLUSIONS

In this study we explored the possibility to incorporate the quality of service in a benchmarking model using as illustration the French electricity distribution sector operated by near hundred DSO belonging to EDF. For this purpose, we estimate an input distance function applying two alternative frontier approaches: parametric SFA and non parametric DEA.

The results, obtained in a multi-dimensional setting, are very close with both approaches and show that in the case under study the incorporation of quality does not have a significant effect upon technical efficiency scores.

Nevertheless, in this analysis we find that the mean shadow price in term of OPEX of one interruption ranges from approximately eight to eleven Euros per year. In other words, electricity distribution operators face a trade-off between network investments and operational expenditures, but they are deeply correlated to the inherent customer density factor.

These results would be useful for regulation design purposes as they could be compared with the customers/society willingness to pay for the level of quality produced by each company.

Table 4
Shadow price estimates for quality and input shadow shares
(by quintiles)

Quintiles	Quality shadow price		Input shadow shares (SFA)		
	SFA	DEA	OPEX	CAP	NINT
SAIFI (number of interruptions per customer per year)					
Q1 [< 0.80]	45.8	80.1	0.055	0.921	0.024
Q2 [0.80-1.03]	16.1	16.1	0.1	0.880	0.020
Q3 [1.03-1.33]	7.4	10.1	0.104	0.883	0.013
Q4 [1.33-1.74]	4.6	4.5	0.123	0.866	0.011
Q5 [> 1.74]	0.9	0.1	0.138	0.858	0.003
Density (customers per km2)					
Q1 [> 7,250]	27.9	14.9	0.148	0.937	0.021
Q2 [6,100-7,250]	11.9	8.8	0.132	0.894	0.018
Q3 [5,100-6,100]	7.1	8.4	0.114	0.872	0.014
Q4 [2,000-5,100]	5.4	12.9	0.88	0.855	0.013
Q5 [< 2,000]	1.9	5.3	0.043	0.847	0.005
% of underground lines					
Q1 [> 52.0]	33.6	10.6	0.043	0.935	0.023
Q2 [37.4-52.0]	11.3	12.6	0.088	0.893	0.019
Q3 [30.4-37.4]	5.7	6.9	0.117	0.872	0.011
Q4 [23.3-30.4]	6.3	21.1	0.124	0.862	0.013
Q5 [< 23.3]	1.5	5.6	0.152	0.843	0.005
All	7.6	10.6	0.105	0.881	0.014

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