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

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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. The analysis in this paper is the first preliminary step in a larger project which is investigating the feasibility of including quality measures into benchmarking models that are often used by regulatory authorities

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1. INTRODUCTION

Although market mechanisms have been introduced in the electricity industry, mainly in the generation and supply activities, the network activities, the so-called wire business, given their natural monopoly aspect still need to be regulated. Regulators are thus required to monitor this wire business operated by Distribution System Operators (DSO) to insure that all market players have a fair access to an essential facility, and plays at the same level playing field

In France, most electricity distribution grids 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[1] 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, as far as concerned quality of supply, customers' connections, 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).

Given the uncertainty about the efficient level of a DSO costs by a regulator, the access charge may be fixed beyond the efficient cost level .

Benchmarking thus may appear as a useful tool for a regulator in assessing the efficiency and the performance of a DSO. 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, they create incentives to 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 compensate the effects of cost reductions on the quality of electricity distribution.

For that purpose, regulators normally rely on tariff and quality incentive schemes. Usually both 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). This penalty or reward is set according to the company effective performance against the desired performance level.

Meanwhile the quality aspect can also be implemented in 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, taken into account its structural constraints and public service obligations.

[1] EDF Réseau Distribution is one of the DSOs which signed concession contracts with municipalities.

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). 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). They also find that TFP growth 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 two studies are to be commended for introducing quality variables into these benchmarking models. However, both studies contain some shortcomings. First, they both make use of TOTEX measures which contain capital expenditure (CAPEX) measures which 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 the monetary values 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 EDFRéseau Distribution in France in the 2003–2005 financial years. In this study, all distribution units are owned 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.

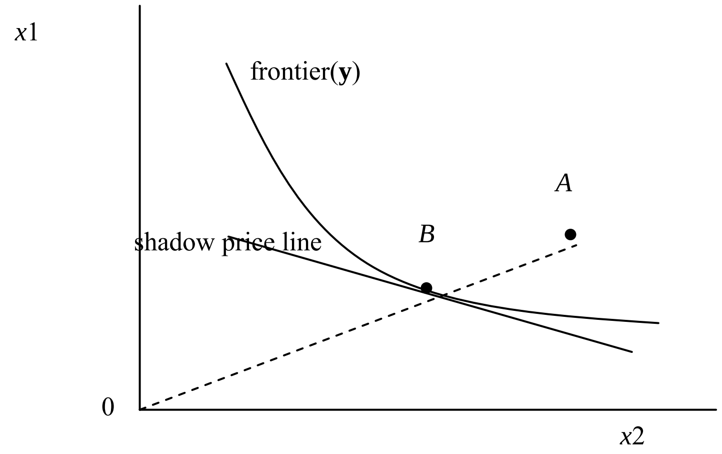
The remainder of this paper is divided in sections. We first present a description of the methodology, followed by a discussion of the data set. We then present the empirical results and finish with some brief concluding comments.

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 ($\mathbf{x}$) can be proportionally reduced while holding the output vector ($\mathbf{y}$) constant. That is, for each data point ($\mathbf{x}$,$\mathbf{y}$) we seek to find the smallest possible value of the scalar θ such that ($\theta\mathbf{x}$,$\mathbf{y}$) 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
Distance function



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 do this.

Following Coelli *et al* (2003), for SFA estimation we use a translog functional form for the input distance function

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

where i denotes the i-th firm in the sample of N firms. We replace the distance term with an error term that has two *i.i.d.* components, $D_i = v_i - u_i$, where $v_i \sim |N(0, \sigma_v^2)|$ is a symmetric error to account for data noise and the $u_i \sim |N(\ \ ,\sigma_u^2)|$ 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. After imposing symmetry and homogeneity restrictions 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.

We also estimate an input distance function using DEA methods. This is a non-parametric method where the frontier surface is a patch-work of facets that are constructed using linear programming methods. The technical efficiency scores are produced as a by-product of the frontier construction process. For further details on DEA, SFA and distance functions in general, see Coelli *et al* (2005).

3. MEASUREMENT OF VARIABLES

The output variables considered for the present study are energy supplied, number of customers and network length.

- The amount of energy supplied (in 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 can not decide the amount of electricity distributed, it has to ensure that all its network assets have the capacity to deliver this energy to all its customers. That's why the total amount of energy supplied may provide a proxy of the number or total capacity of transformers that have to be installed and operated on the network. In our studyn we have considered the gross electricity distributed units, including losses which are payable by DSOs in France.
- The number of low voltage 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. Besides, a large part of distribution activities relating to metering services, customer connections, customer calls, billing,…, are directly correlated to the number ofLVcustomers. Industrial customers who are connected to Medium Voltage (MV) network have not been taken into account because this their power demand is more important than their number as a cost driver in a distribution company.
- Finally, network length (NETL) 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 for overhead lines, …, are closely linked to the length in kilometers of MV and LV lines. Moreover, the reliability of a distribution network and therefore the level of quality of supply strongly depend on the length of the feeders. In big cities, where the feeders are mostly short and underground, the number of outages should be lower than in few dense areas with a high proportion of overhead lines. As a consequence, the costs of repairs can not be the same in urban or rural areas. Service area (km^2) can also be considered as a good indicator of the structural environment where the utility has to operate. In this study, some models have been carried out with the service area as an output variable, instead of network length. Similar results have been achieved.

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 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 these three outputs can not reflect the exact efficiency of operational expenses which couls result from environmental differences: proportion of grids in forests or mountains, city surplus costs, age of the assets, accessibility of lines or substations, climatic events, …

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. In the scope of the current study, such an assumption has a full meaning since all the data come from a single distribution operator. EDF Réseau Distribution defines and manages the same policies for investment, operations and network asset development. The asset age profile is then quite homogeneous between all EDF 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 OPEX represent direct operational costs of local distribution units, out of centralized network service support and overhead costs and out of depreciation of grid assets. These operational costs include all 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, …
    - running connections services,
    - providing meter services and any other customer interventions,
    - relations with local authorities, customers.

  We could have chosen to split this 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. Besides, practices in terms of outsourcing do not differ a lot among the EDF local distribution units.

- 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. Actually, the total number of interruptions NINT has been calculated as followed:

  NINT = SAIFI*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 (works).

Exceptional events have been excluded in order not to disadvantage ditribution units which had to face with major climatic events (big storms, floods, …) in the study period.

Descriptive statistics for the variables used in this study are presented in Table 1.

Table 1
Descriptive statistics

Variable		mean	st. dev.	min.	max.
CUST	y1	324857	134162	109435	762905
NETL	y2	13359	6165	4060	32743
GWH	y3	3557	1477	1001	7976
OPEX	x1	22194	8222	10575	57591
CAPITAL	x2	626924	215874	250001	1212792
NINT	x3	390420	249524	49901	1927519

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

4. EMPIRICAL RESULTS

The “base model” output variables are CUST, NETL 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 base model are listed in Table 2. 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), but we note that those for NINT and GWH are rather small. Ray scale economies are calculated as the negative of the inverse of the sum of the output elasticities. This equals 1.12 indicating mildly increasing returns to scale at the sample mean.

Table 2
SFA estimates

Var.	Model 1		Model 2		Model 3	
	Coef.	**t-ratio**	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**
Inter.	0.118	(13.51)	0.118	(13.21)	0.116	(12.9)
x1	0.094	(*)	0.106	(*)	0.112	(*)
x2	0.906	(60.79)	0.892	(53.14)	0.874	(53.1)
x3	-	-	0.002	(0.84)	0.015	(2.4)
x1x1	-0.149	(*)	-0.181	(*)	-0.187	(*)
x2x2	-0.149	(2.5)	-0.143	(2.3)	-0.064	(0.9)
x3x3	-	-	-0.003	(0.7)	-0.019	(1.3)
x1x2	0.149	(*)	0.160	(*)	0.116	(*)
x1x3	-	-	0.021	(*)	0.071	(*)
x2x3	-	-	-0.018	(1.6)	-0.053	(2.3)
y1	-0.454	(16.10)	-0.458	(15.7)	-0.465	(16.2)
y2	-0.398	(27.43)	-0.40	(24.8)	-0.391	(21.7)
y3	-0.065	(2.71)	-0.058	(2.6)	-0.054	(2.5)
y1y1	-0.352	(1.9)	-0.351	(1.8)	-0.258	(1.5)
y2y2	0.044	(0.92)	0.060	(1.1)	0.070	(1.2)
y3y3	-0.104	(0.64)	-0.046	(0.28)	0.072	(0.5)
y1y2	0.182	(3.7)	0.174	(2.96)	0.146	(2.6)
y1y3	0.190	(1.15)	0,160	(0.94)	0.048	(0.3)
y2y3	-0.090	(2.18)	-0,104	(2.1)	-0.086	(1.9)
x1y1	-0.082	(*)	-0.119	(*)	-0.186	(*)
x1y2	0.030	(*)	0.033	(*)	0.050	(*)
x1y3	0.048	(*)	0.078	(*)	0.116	(*)
x2y1	0.082	(1)	0.141	(1.5)	0.236	(2.5)
x2y2	-0.030	(1,15)	-0.034	(1.3)	-0.064	(2.3)
x2y3	-0.048	(0.62)	-0.101	(1.2)	-0.175	(2.0)
x3y1	-	-	-0.022	(1.52)	-0.050	(1.7)
x3y2	-	-	0.001	(0.14)	0.015	(1.6)
x3y3	-	-	0.024	(1.65)	0.059	(2.2)
σ	0.020	(6.9)	0.020	(6.09)	0.020	(6.1)
γ	0.988	(418.1)	0.990	(410.5)	0.989	(414)

(*) Parameter computed applying homogeneity conditions.
Model 1: without quality; Model 2: Minutes of interruptions (MINT); Model 3: # of interruptions (NINT).

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

model	mean	st. dev.
base SFA	0.894	0.072
base DEA	0.907	0.082
no quality SFA	0.896	0.072
no quality DEA	0.898	0.083

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 7.9 from the SFA model suggests that the marginal cost of reducing one interruption (on average) would be 7.9 Euros. However, we note that the DEA estimate is 50% larger than this SFA estimate 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, as one would expect.

Table 4
Shadow price estimates for NINT
quality variable (based on OPEX price)

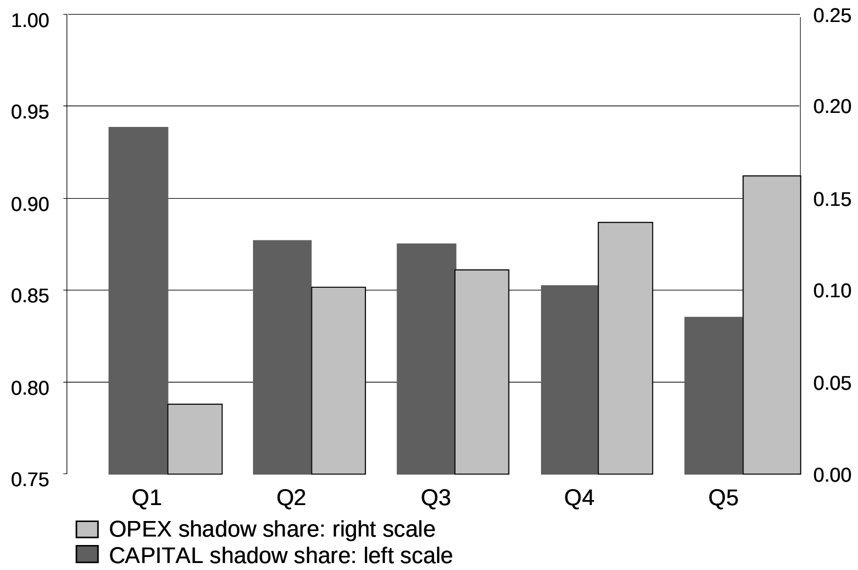
Group	SFA	DEA
All	7.4	11.8
Quintile 1 [< 0.800]	64.6	54.8
Quintile 2 [0.800-1.030]	17.4	17.0
Quintile 3 [1.030-1.330]	7.8	17.7
Quintile 4 [1.330-1.740]	4.1	4.6
Quintile 5 [> 1.740]	0.7	0.2

Note: Quintiles are by NINT/CUST.

In Figure 2 average OPEX and CAPITAL shadow shares by NINT/COST quintiles are plotted using SFA estimations. They correspond to the partial elasticities of the distance function with respect OPEX and CAPITAL, 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.

Figure 2
OPEX and CAPITAL shadow shares



Note: SFA model estimates. Quintiles are by NINT/CUST.

5. CONCLUSIONS

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

Furthermore, we find that in the case under study the incorporation of quality does not have a significant effect upon technical efficiency scores. This analysis is the first preliminary step in a larger project which is investigating the feasibility of including quality measures into benchmarking models.

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