Efficiency benchmarking and remuneration of Spanish electricity distribution companies

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Abstract: In Spain, the average remuneration of large electric distribution companies is much lower than that of smaller ones, which leads us to wonder if the smaller ones are managed efficiently. A meta-frontier DEA model is calculated in order to benchmark, in terms of remuneration and quality, different clusters of distributors that present different technologies. The sample is composed of 236 distributors (including the five largest units). The savings for the system would be approximately 174 million Euros per year. Moreover, compensation regulation should aim to guide distributors towards their respective intra-cluster frontiers.

Keywords: DEA Meta-frontier analysis; Spanish electricity distributors; Regulation.

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1. Introduction.

The concept of meta-frontier is related to the early concept of the meta-production function as defined by Hayami and Ruttan (1970). This function is also implicit in previous works such as those by Salter (1960), Brown (1966), or Nelson (1968). Hayami and Ruttan (1970) state that: "*The meta-production function can be regarded as the envelope of neoclassical production functions.*" These authors based their reasoning on the fact that, in the long term, all companies have access to all potentially discoverable technical alternatives. Since the publication of these seminal works, the concept of meta-frontier has been extended in at least two directions: the convenience of using non-convex meta-frontiers, and the existence of different operational conditions which restrict the level of productivity of the different units.

Among the studies which have focused on the convenience of using non-convex meta-frontiers, we can highlight the following: Afsharian (2017) proposes an extension of the stochastic nonparametric envelopment of data (StoNED) approach to estimate the meta-efficiencies of both convex and nonconvex meta-frontiers. Amsler *et al.* (2017) evaluate the meta-frontier distance using a stochastic frontier model. Walheer (2018) points out the drawbacks of using the arithmetic average as an aggregation method to measure the technology gap ratio at the group level and proposes an alternative aggregation based on a linear weighting aggregation procedure. Afsharian and Podinovski (2018) simplify the benchmarking setting of the DMUs against the common non-convex meta-frontier by solving a single linear program. Furthermore, their dual model is useful in identifying the return-to-scale of efficient units on the meta-frontier. For their part, Kerstens *et al*. (2019) delve into the disadvantages of assuming convex meta-frontier, developing a refined methodology for nonparametric envelopment of non-convex metasets. Their approach is applied to a hydroelectric power plant data set in order to show that the assumption that 'the convexification strategy is empirically innocuous' is false. Likewise, Jin *et al*. (2020) continue in the line of the previous work, analyzing the disadvantages of convexification when using the Malmquist and Hicks–Moorsteen productivity indices.

The meta-frontier has also been extended to take into account not only the existence of different levels of technical knowledge among the different units but also the existence of different operational conditions which restrict the level of productivity of each unit. According to Simar and Wilson (2015), these may reflect different conditions such as ownership, regulatory constraints, and business environment. Such factors are neither inputs nor outputs and are not under the control of the firm; however, they may influence the production process.

The existing literature on the efficiency level of units that function under different operational conditions can be classified into two groups, depending on whether or not they assume the so-called separability condition. Under this condition, environmental factors (*Z*), also called operational conditions or contextual variables, influence neither the shape nor the level of the production frontier, and the potential effect of *Z*-variables on the production process is only through the distribution of the inefficiencies. Thus, under the separability condition, the environmental variables Z influence the mean and variance of the efficiency scores, but not the boundary of the inefficiency process. A connotation of the separability condition is that its compliance implies that the production technology is the same for all productive units, regardless of their environmental conditions (homogeneous technology). However, if the condition is not met, different technologies are generated because the environmental factors of each unit (or group of units) limit their own set of production possibilities (heterogeneous technology) –on this condition, see, for instance, Simar and Wilson (2007, 2015), Bădin *et al.* (2012), Daraio *et al.* (2015), Bjønrdal *et al.* (2016), Seifert (2016).

Simar and Wilson (2007) suggest that the fulfillment of this condition justifies second-stage regressions in which nonparametric estimates of productive efficiency (typically obtained by data envelopment analysis, DEA) are regressed on environmental variables in order to account for exogenous factors that might affect firms' performance (normally using OLS or Tobit regression). In the one-step approach, environmental variables are included directly in the estimation of the efficiency itself. According to these authors, in many second-stage estimates within empirical literature, the statistical inference is invalid due to the existence of serial correlation among the estimated efficiencies; the truncated regression, not the tobit regression, is the correct model in their experiments. In this line, Daraio *et al.* (2015) provide a nonparametric test to contrast the assumption required in two-stage estimations; that is, the second-stage environmental variables cannot affect the support of the input and output variables in the first stage.

Other studies have assumed that the production technology can be substantially different among individuals or units (such as countries or firms), in this way, breaking with the condition of separability. Different technologies arise when the sample units differ in terms of development level or operational/environmental conditions. To O'Donnell *et al.* (2008), a common meta-frontier exists and is defined as the boundary of an unrestricted technology set; at the same time, there are group frontiers, which are the boundaries of restricted technology sets, where the restrictions derive from lack of economic infrastructure or other characteristics of the production environment. Kneip & Simar (1996) anticipate, to some extent, the idea of meta-frontier presented by O'Donnell *et al.* (2008), since those authors use kernel methods to estimate individual production functions in a panel-data on firms, and define the production frontier as the envelope of these individual functions.

In this article, we extend the analysis of Arcos *et al*. (2017) by abandoning the assumption of separability to analyze the electrical distribution industry in Spain. When one thinks about the electrical industry sector, it is easy to understand that there are different generation technologies, but the existence of different technologies in the electricity distribution business is more debatable; after all, distribution is only responsible for feeding electricity from generation units to supply points. These differences in distribution are not due to technical reasons but to the existence of different operational/environmental conditions. In the case of Spain, more than 300 distributors operate with very different conditions: substantial size differences, different types of customers (residential/industrial), and different performance areas (smaller vs. larger and urban vs. rural), which justifies that not all companies face the same production possibility set, even in the long term.
In the empirical literature on frontier analysis for the electrical distribution industry, when the separability condition has not been assumed, the measurement of the individual efficiency has been conducted either through parametric, nonparametric or semi-nonparametric techniques. For instance, Seifert (2016, ch. 5) compares three frontier approaches to account for the influence of external factors in a production setting: nonparametric conditional DEA (cDEA, Daraio and Simar, 2005 and 2007), parametric latent class SFA (LC-SFA, Greene, 2005; Orea and Kumbhakar, 2004) and stochastic semi-nonparametric envelopment of *Z* variables data (StoNEZD, Johnson and Kuosmanen, 2011). According to this author, contrary to cDEA, LC-SFA does not generate reference units; that is, the frontier reference points in the model do not indicate which firms are used to set the benchmarks; this can be inconvenient if the regulator requires clearly identified reference units. In our review, we have mainly found works which estimate stochastic meta-frontier models, such as Huang *et al*. (2010) and Li *et al*. (2017), that estimate stochastic cost frontier models for panel data which separate sample units (the first paper) or sub-periods (the second one) in different homogenous groups. Likewise, Cullmann (2012), Agrell *et al*. (2013), and Orea and Jamasb (2014) estimate different latent class stochastic frontier models for panel data, while the first author estimates a distance function, the others estimate cost functions. In latent class models, the classification of the units in different technological groups is not based on a priori sample separation criteria; however, the model itself accounts for the heterogeneity among units by endogenously sorting them into a pre-specified number of groups.

There are, however, few studies that use the DEA meta-frontier to explore electrical distribution, and even less that combine this methodology with cluster analysis, as is the case in our study. For example, Bjørndal *et al*. (2016) solve a conditional DEA using a dataset of 123 distribution companies (DisCos) in Norway in a Revenue Cap framework (they use average data for the period 2008-2012). This nonparametric model does not calculate a meta-frontier itself but is close to the DEA meta-frontier model in the sense that it does not require the separability condition and restricts the selection of units to be compared to those with a similar environment. According to these authors, conditioning a firm's production process on its operational environment gives us a better yardstick for determining its efficient cost; their model allows us to distinguish between managerial inefficiency and operational heterogeneity. Another work that is close to our methodological approach is that of Dai and Kuosmanen (2014) which, like us, combines frontier estimation and clustering methods (specifically, it combines the SToNED model with the clustering algorithm based on normal mixture models). These authors applied a cluster-specific framework to the Finland electricity distribution networks (the data consists of six-year average input-output values over the period 2005-2010), and the results are compared with those obtained from traditional DEA. The clustering-based method is shown to effectively characterize each group, giving rise to the concept of 'relative benchmark'; compared with DEA, the clustering approach provides more references for each decision-making unit (DMU), and targets with higher efficiencies can be identified.

As previously commented, our study extends the analysis of Arcos *et al*. (2017). These authors applied the DEA methodology to estimate a remuneration-frontier for a representative sample of 102 smaller DisCos in Spain (in the year 2011). Given that there is a large size dispersion (5 very large firms and more than 300 firms of large, medium, small, or very small size), the five very large companies are excluded from the analysis, obtaining potential savings of 75% of the total remuneration of the companies analyzed, thus giving an idea of their reduced efficiency. These authors do not apply the concepts of meta-frontier or cluster-frontier, only solving a traditional DEA model that excludes the largest companies.

In our opinion, given the existing literature on nonparametric meta-frontier models applied to electricity distribution, this work is novel for two reasons: firstly, it helps to fill a gap in the empirical and methodological literature about efficiency measurement in the electrical distribution industry; indeed, there is little literature on cluster-based meta-frontier analysis applied to this sector (versus power generation, for example) and is biased towards parametric models in recent years. Secondly, from an economic perspective, we analyze an idiosyncratic sector (Spanish electricity sector) where electricity distribution operates independently (unbundled) of the rest of the activities of the electrical industry (generation and supply), and consists of more than 300 distributors which have varying sizes and operate in areas that can become very different (rural vs. urban, for example).

As with Arcos *et al*. (2017), we change the efficiency perspective from the individual firm to the Regulatory body, that is, the DMUs are the DisCos, but the information provided by our benchmarking cost-frontier model is oriented to reducing remuneration of inefficient units (maintaining quality), with the corresponding savings for the overall system. However, unlike these authors, our analysis takes into account the operational *Z*-conditions of the companies when carrying out the comparative process. According to Bogetoft (1997), when there is uncertainty about the DMU technology and asymmetry of information between the regulator and the regulated units, the DEA methodology, specifically, the DEA-based yardstick competition (DBYC), can play an important role in encouraging cost reductions. In this line of frontier-based regulation, Agrell and Bogetoft (2016) reformulate the classical CRS model to determine a common set of weights for all units, so that the overall efficiency is maximized. The sector-wide efficiency is then a result of compromising the scores of more specialized smaller units, which also gives a more stable set of weights. This Centralized Resource Allocation (CRA) DEA (Lozano and Villa, 2004) could stimulate collective bargaining on cost efficiency under regulation with asymmetric information on relative prices and costs. Our regulator-oriented approach can also be related to the field of central management. For instance, Varmaz *et al*. (2013) transfer the concept of DBYC to intra-organizational performance management. Their approach is centered on computing a form of super-efficiency for each unit, applying a variant of the CRA-DEA model of Lozano and Villa (2004). The model allows incorporating both internal dependencies between DMUs (German retail banks) and external observations. Their model simultaneously calculates optimal strategies for every single branch and the systems' overall performance. More recently, Afsharian *et al*. (2017) argue that the approach of Varmaz *et al*. (2013) can lead to inconsistent results, incompatible with individual incentives since their super-efficiency measure does not capture the impact of a unit on the system as a whole because the system is not defined in a stable manner.

Finally, at the methodological level, we provide a new configuration of efficiency analysis and clustering methods when used in combination for benchmarking purposes. Specifically, we combine the *k*-means cluster analysis (with the determination of the optimal number of clusters) with a meta-frontier DEA model. In this last model, we control the fact that the output indicator measuring the quality in the distribution service can take negative values. As would be expected, the savings proposed to the system in this work are less than those achieved in Arcos *et al.* (2017), since they compare with the overall efficiency rather than that of the specific groups. Note that when Dai and Kuosmanen (2014) propose to compute the efficiency score for the whole dataset using StoNED and then group the DMUs using a mixture model clustering algorithm, they give rise to a scenario in which the units of each cluster are compared, both inside and outside their cluster, in terms of a single efficiency that has been calculated globally. Our model allows each unit to be compared against two types of efficiencies; the one generated into its own cluster and the one given by the underlying meta-frontier.

The rest of the article proceeds as follows: after this introduction, section 2 briefly describes the electricity distribution system in Spain and how the DisCos (Distribution Companies) are compensated. Section 3 provides an explanation of the meta-frontier DEA methodology. For its part, section 4 makes a description of the data used in the analysis and carries out a clustering process to get homogeneous groups of firms. Section

5 presents the proposed meta-frontier remuneration model and discusses the main findings obtained in terms of both monetary savings and quality of service. Finally, Section 6 contains the main conclusions of our study.

2. The remuneration system in Spain.

Currently, Spanish electricity distribution is organized into 347 companies, which serve almost 29 million users. The size of the companies is based on two different models: very large companies, which supply power to 97% of the users and take energy from the generation and transmission system; and smaller companies, 342 in total, which serve an average of 30,000 supply points and feed from lower voltage levels. These smaller companies are the result of private initiatives that emerged at the end of the 19th century, they did not participate in the process of industrial integration during the second half of the 20th century but were limited to local distribution. Some of these small companies, which were born one hundred years ago of private initiative, without adequate technical and financial capabilities, began merger and acquisition processes that shaped the current map of Spanish electricity distribution.

In Spain, as in many other countries, the activities of generation, transmission, distribution, and commercialization of electricity were separated at the end of the last century (Electricity Sector Law 54/1997), differentiating those activities that had natural monopoly characteristics (transmission and distribution) from those of a competitive nature (generation and supply). This fact led from the development of the activity through vertically integrated companies (which covered their costs with electricity sales tariffs approved by the Regulator) to a more complex structure in which monopolistic activities became regulated under strict supervision by the Public Administration in order to ensure that they gave symmetrical treatment to all the agents in the system.

This new situation caused them to move from operating with a cross-subsidy structure (the benefit of some activities compensated for losses in others) to a regulated remuneration scheme based on the principle of sufficient revenue (Viscusi *et al*., 1995). The revenue received by the distributing company must cover the efficient costs necessary to develop its activity, including: i) network investments (depreciation and financial return), ii) operation and maintenance costs, iii) administrative costs (management, taxes, and fees) and iv) commercial costs (such as metering and billing of tolls). The regulatory model adopted in Spain is a Revenue Cap, which is based on incentives (Laffont and Tirole, 1993). In this model, the Regulator calculates the revenue that each distribution company must have, following the formula below:

$$\begin{aligned} R_{i,n} &= \left(R_{i,n-1} - Q_{i,n-2} - P_{i,n-2}\right)(1 + AI_n) + \left(Y_{i,n-1} + Q_{i,n-1} + P_{i,n-1}\right) \Rightarrow \\ \Rightarrow R_{i,n} &= R_{i,n-1}(1 + AI_n) + Y_{i,n-1} + \left[Q_{i,n-1} - Q_{i,n-2}(1 + AI_n)\right] + \left[P_{i,n-1} - P_{i,n-2}(1 + AI_n)\right] \end{aligned} \quad (1)$$

where $R_{i,n}$, is the remuneration for the Distributor i in year n, Q and P are incentives associated with quality of service and electrical losses respectively, AI_n is a price actualization index, and $Y_{i,n-1}$ represents the increase in remuneration associated with the new installations brought into service in the previous year (*n–1*) by the company. The facilities must be proposed *ex-ante* by the distribution company, justifying them on the basis of electricity demand and available network. This investment plan must be authorized by the regional government and by the national Regulator, who compare the proposal with a theoretical network model. This theoretical model proposes an increase in the DisCo remuneration, which has to be enough to cover the operational and capital costs; the calculations are made for a period of five years. It assumes the locations of current supply points, creating an optimal theoretical network that minimizes long-term supply costs. A detailed explanation of this mechanism can be found in Gómez *et al*. (2011).

Since investments in the distribution network usually are long-lived projects (typically 40 years), the value of component $Y_{i,n-1}$ is relatively low, and therefore misalignments in the calculation of past remuneration values ($R_{i,n-1}$) will take many years to be corrected. On the other hand, it should be noted that the values of quality and losses incentives (Q and P) are significantly lower than the rest of the terms in the formula. In these circumstances, although a published calculation remuneration method is available, its application is not very transparent and, sometimes, it is difficult to explain the remuneration results obtained. In any case, it seems proven that the Revenue Cap model stimulates companies to reduce their costs, allowing them to obtain greater benefits (Joskow, 2014).

The idiosyncratic structure of electricity distribution in Spain, together with its particular remuneration model, makes it difficult to explain the differences in remuneration that exist between companies of different sizes. As we will see below, the remuneration given by equation (1) constitutes the key input in our meta-frontier DEA model, since we consider that, among a group of similar companies, the one that offers the service requiring the lowest remuneration is the most efficient for the system and society as a whole. Note also that formula (1) in itself does not allow input/output efficient units to be identified in a certain period *n*, since the remuneration in period *n* is based on past values (*n*–1, *n*–2) of the remuneration itself, the quality of the service and the investments carried out.

3. DEA approach.

DEA is a nonparametric linear programming based technique for evaluating the relative performance of similar units, a.k.a. Decision-Making Units (DMUs) (Cooper *et al.*, 2004). These DMUs consume inputs and produce outputs. The basis of the DEA methodology is the derivation of a Production Possibility Set (PPS) from the inputs and outputs corresponding to the observed DMU. The PPS contains all operating points that are feasible. In the case of the CRS and VRS technologies, the PPS assumes as feasible the operation points that are the linear combination and the convex linear combination of existing DMUs, respectively. Once the PPS has been identified, the aim is to look for an efficient unit belonging to the PPS onto which the observed DMUs can be projected. There are two ways to identify efficient units: those able to produce either the same amount of output using less input (input orientation) or more output using the same amount of inputs (output orientation).

Considering a problem with $j = 1, ..., n$ DMUs; $r = 1, \ldots, p$ outputs and $i = 1, \ldots, m$ inputs. The input-oriented model, in its envelopment form, is formulated as following,

$$
\begin{aligned}
& Min\ \ \theta_0 \ \ - \epsilon\left(\sum_{i=1}^{m} s_{i0}^{-} + \sum_{r=1}^{p} s_{r0}^{+}\right) \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j x_{ij} = \theta_0 x_{i0} - s_{i0}^{-} \quad \forall i = 1, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} = y_{r0} + s_{r0}^{+} \quad \forall r = 1, \ldots, p \\
& \sum_{j=1}^{n} \lambda_j = 1 \qquad\qquad (*) \\
& \lambda_j \geq 0 \quad \forall j = 1, \ldots, n \\
& \theta_0\ free \\
& s_{i0}^{-}, s_{r0}^{+} \geq 0 \quad \forall i = 1, \ldots, m; \ \ \forall r = 1, \ldots, p
\end{aligned}
\tag{2}
$$

where x_{ij} and y_{rj} represent the consumption of input *i* and production of output *r* of DMU_j. Variables λ_j mean the intensity variables for the convex linear combination of observed DMU_0, variable θ_0 represents the radial reduction of all the inputs consumed by DMU_0 given a level of outputs. On the other hand, s_{i0}^{-} and s_{r0}^{+} represent the additional reductions and increases in inputs and outputs, respectively, following the radial reduction. Finally, the term ϵ is a very small constant that establishes a two phases resolution of the model (first variable θ_0 is minimized, and then the sum of slack variables is maximized).

The variable θ_0 represents the technical efficiency under the CRS assumption, and in such a case, the model is known as CCR-INPUT (Charnes *et al.,* 1978). However, when the problem exhibits VRS, the constrain labeled with the asterisk must be added. This model is known as BCC-INPUT (Banker *et al.,* 1984).

A DEA model is translation invariant when the translation of the original data values results in a new model that is equivalent to the model using the original data. Pastor (1994) provides a translation invariance classification of basic DEA models, showing that the BCC-INPUT model is invariant under the translation of outputs.

On the other hand, most DEA models assume that inputs and outputs are semi-positive, i.e., all data are assumed to be non-negative, but at least one component of every input and output vector is positive (Cooper *et al.*, 2000). However, in some cases, this assumption fails, such as, for instance, when a variable could take negative values (temperature in ºC) or when it is measured as a difference from one period to another (growth of the number of clients). In the presence of a translation-invariant DEA model, it is always possible to translate the negative data and solve the model as if the data were positive (Pastor and Ruiz, 2007).

DEA models also deal with inputs or outputs that can be not varied at the discretion of the individual DMUs, that is, "non-discretionary" variables. For those cases, the approach proposed in Banker and Morey (1986) should be applied:

$$
\begin{aligned}
& Min \quad \theta_0 - \varepsilon\left(\sum_{i\in I_D} s_{i0}^- + \sum_{r\in O_D} s_{r0}^+\right) \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j x_{ij} = \theta_0 x_{i0} - s_{i0}^- \qquad \forall i \in I_D \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} \qquad \forall i \in I_{ND} \\
& \sum_{j=1}^{n} \lambda_j y_{rj} = y_{r0} + s_{r0}^+ \qquad \forall r \in O_D \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} \qquad \forall r \in O_{ND} \\
& \sum_{j=1}^{n} \lambda_j = 1 \qquad (*) \\
& \lambda_j \ge 0 \qquad \forall j = 1, \dots, n \\
& \theta_0 \; free \\
& s_{i0}^-, s_{r0}^+ \ge 0 \quad \forall i \in I_D; \;\; \forall r \in O_D
\end{aligned} \tag{3}
$$

where the symbols *D* and *ND* represent "Discretionary" and "Non-discretionary" respectively. The model sets variables that try to optimize the inputs and outputs only for discretional dimensions. Again, the constrain with an asterisk will be omitted in the CRS case.

When the observed DMUs can be divided into groups 'g' according to the different production possibilities (sub-technologies) in which they are operating, it is possible to evaluate the technical efficiency with respect of each sub-technology as follows (O'Donnell *et al.*, 2008):

$$
\begin{aligned}
& Min \;\; \theta_0^g \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j^g x_{ij}^g \le \theta_0^g x_{i0}^g \quad \forall i = 1, \dots, m \\
& \sum_{j=1}^{n} \lambda_j^g y_{rj}^g \ge y_{r0}^g \quad \forall r = 1, \dots, p
\end{aligned} \tag{4}
$$

$$\sum_{j=1}^{n} \lambda_j^g = 1$$
$$\lambda_j^g \geq 0 \quad \forall j = 1, \dots, n$$
$$\theta_0^g \ free$$

Note that an input orientation has been assumed. Once the model (4) is solved, a meta-frontier ratio can be computed as:

$$MFR_0^g = \frac{\theta_0^{META}}{\theta_0^g} \tag{5}$$

where θ_0^{META} is the meta-distance function or "meta-efficiency," and it is computed using (2) when all the DMUs are considered. On the other hand, θ_0^g is called the "within-group efficiency" and, since $\theta_0^{META} \leq \theta_0^g$, the meta-frontier ratio can be interpreted as a percentage. Specifically, expression (5) means that, given the output vector, the minimum input that could be consumed by a DMU from group k is MFR_0^g (%) of the input that is feasible using the meta-frontier. It is important to note that it is not necessary to compute the second phase in (4) to obtain the meta-frontier ratio.

4. Data description.

The analysis proposed in this study consists of measuring, using the DEA meta-frontier technique, the efficiency of a sample of 236 electricity distributors in Spain in the year 2016. The Spanish Ministry of Industry publishes in the Official State Bulletin (BOE) annual information on the remuneration of the distribution companies, as well as on their quality of service, assets, and urban/rural nature. The information about points of supply and distributed energy has been collected from the companies' websites. Due to the difficulty of obtaining this last information, it has not been possible to cover the entire population (347 firms) for several years. However, our sample represents 68% of Spanish distribution companies and 99% of the total energy supplied.

Table 1. Sample description.

Variable	Mean	Std. Dev.	Min	Max
Remuneration (€ millions)	21.2	176.3	0.026	2,023.2
Distributed energy (GWh)	978.3	8,530.0	0.095	95,709.7
P.o.S (Units)	121,305.9	1,072,967.0	20.0	11,900,000
Assets (€ millions)	315.2	2,777.4	0.086	33,380.3
TIEPI (Hours)	1.47	1.1	0.1	6.7
Ratios				
Remuneration per distributed energy (€/MWh)	137.5	91.8	18.2	736.1
Remuneration per P.o.S. (€ / unit)	454.8	1,218.1	152.9	17,371.1
Remuneration per Assets (€ / €)	0.154	0.078	0.042	0.576
Distributed energy per P.o.S. (kWh / unit)	3,513.1	4,657.7	320.3	67,847.3

There is a high standard deviation in the analyzed variables. That is, although the average distributor annually receives remuneration of 21.2 million euros, distributes close to 1000 GWh, has more than 120,000 supply points, and has assets valued at 315.2 million euros, approximately 90% of the distributors earn less than 3 million euros a year and has less than 2000 points of supply (P.o.S). To measure the quality of the service, we use the variable called *Tiempo de Interrupción equivalente por Potencia Instalada* (TIEPI, Time of Interruption Equivalent to the Installed Power in Medium Voltage). TIEPI is the official indicator of the quality of service in Spain and takes values of the same order as the SAIDI (System Average Interruption Duration

Index), which is the standard international index. This indicator has an average value of 1.47 hours in our sample, although the company with the highest TIEPI (a very small and mainly rural one) reaches a value of 6.7 hours in the year analyzed.
In terms of unit remunerations, the representative company has a remuneration per MWh delivered, per P.o.S. and per asset euro of 137.5, 454.8, and 0.154 euros, respectively; the standard deviations of these ratios are smaller than in the case of the absolute variables. Finally, the average energy distributed annually to each supply point amounts to 3,513.1 KWh, although this value varies between companies from 230.3 kWh to 67,847.3 kWh; it must be taken into account that in the sample there are residential and industrial clients.

5. Inputs, outputs, and external factors. Cluster analysis.

The variables used in the DEA meta-frontier analysis have been, for each DMU: the total remuneration received, the total level of fixed assets, the distributed energy, the number of connection points, and a variable describing the evolution of the quality index TIEPI.

There is no clear agreement on what combination of input and output variables best describes the performance of the electricity distributors, as this combination depends on how the efficient unit is defined. The discretional input variables most commonly used are operating costs (OPEX), total costs (TOTEX) (Giannakis *et al.,* 2005, Cullmann and von Hirschhausen, 2008, Jamasb and Pollitt, 2003, Coelli *et al.*, 2008, Costa *et al.*, 2015, Kuosmanen, 2012, Dai and Kuosmanen, 2014, and Sánchez-Ortiz *et al*., 2020) and the number of employees (Cullmann and von Hirschhausen, 2008, Zhang and Bartels, 1998, Ghaderi *et al.*, 2006, von H. *et al.*, 2006, and Mullarkey *et al.*, 2015). Typically, these DEA models adopt an input orientation. The capital input of the company (usually approximated by variables such as the transformation capacity, the maximum load, or the network length) has been considered as a non-discretionary input.

The typical outputs in the literature have been the energy supplied to the customer, the number of P.o.S., the network length, and certain variables related to the quality of service, such as the number of interruptions or the cumulative duration of such interruptions –see for instance Blázquez-Gómez and Grifell-Tatjé (2011), Giannakis *et al*. (2005), Cullmann and von Hirschhausen (2008), Zhang and Bartels (1998), Jamasb and Pollitt (2003), Ghaderi *et al*. (2006), von H. *et al.* (2006), Coelli *et al.* (2008), Costa *et al*. (2015), Kuosmanen (2012), Dai and Kuosmanen (2014), Mullarkey *et al*. (2015) and Sánchez-Ortiz *et al*. (2020). In general, the studies which consider service quality assume that an undesirable output, such as the number or the duration of supply interruptions, can be treated in the model as an input (see, for example, Ahn *et al.,* 2019).

An important issue when measuring the efficiency of distributors is the presence of environmental variables, which represent external factors that are beyond the control of the production units but which influence their performance. The typical environmental or contextual variables in the analysis of electrical distribution are: the dispersion of P.o.S. (usually approximated by the number of P.o.S. per km^2 of service area); the network density (number of P.o.S. per km of the network); the service area (km^2); the type of service area (rural or urban); the type of customer (such as residential or industrial and low voltage or medium voltage); the type of cable (aerial or underground); the distinction of different geographical (or economic) areas within the country analyzed; and the weight of the industrial sector in the GDP –in this regard, see the works of von H. *et al*. (2006), Cullmann and von Hirschhausen (2008), Coelli *et al*. (2008) and Mullarkey *et al*. (2015).

This work follows the input/output approach of Arcos et al. (2017) –although expanding their model to a meta-frontier context. The general idea is to evaluate whether or not the amount of income that the distribution companies receive is adequate for the quality and quantity of energy delivered (each operating with a particular capital structure). Observe that we take the regulator's point of view, rather than that of the individual firm. Moreover, the contextual variables existing in the literature are closely related to the size of the company and its scope of operation (for example, rural vs. urban); such variables will be taken into account when calculating the meta-frontier.

In order to develop the meta-frontier analysis, the strategy followed has been to generate clusters of distributors that are characterized by being internally homogeneous and externally (each cluster with the others) heterogeneous. Each cluster of distributors being sufficiently idiosyncratic, one can assume the existence of a particular production frontier for each of them; that is, one can assume that the separability condition is not satisfied. To carry out the grouping process, we have used the *k*-means clustering technique using the variables that will have a contextual (non-controllable) role in the DEA model to be solved in the next section. The k-means clustering is an iterative procedure that separates the data into k groups or clusters. The procedure begins with k initial group centers (randomly selected) so that observations are assigned to the group with the closest center. Therefore, the average of the observations assigned to each of the groups is computed, and the assignment process is repeated. These steps will continue until all observations remain in the same cluster when a new iteration is carried out (on the k-means methodology see, for example, Jain, 2010, Everitt *et al.,* 2011, and Makles, 2012). It is well known that the k-means clustering process works well when the shape of clusters tend to be hyper-spherical; the clear differentiation by size and operation area of Spanish distributors seems to be compatible with this scenario.

The contextual variables for which we have information refer to the size of the companies and to the type or types of zones in which they operate. Specifically, the variables related to the size are (1) the connection points, (2) the distributed energy, and the monetary value of (3) high-voltage gross fixed assets, (4) low-voltage gross fixed assets, and (5) other necessary fixed assets, such as offices, control rooms, communications, and IT systems; these three fixed assets define the capital structure of each unit.

Regarding the type of zone, they are currently defined in the Spanish standards (Article 99 of RD 1955) as follows:

1. Urban area: a set of municipalities in a province with more than 20,000 P.o.S., including provincial capitals, although they do not reach the previous figure.
2. Semi-urban zone: a set of municipalities in a province with a P.o.S. total of between 2,000 and 20,000, excluding provincial capitals.
3. Concentrated rural area: a set of municipalities in a province with a P.o.S. total of between 200 and 2,000.
4. Dispersed rural area: a set of municipalities in a province with less than 200 P.o.S., as well as supplies located outside population centers that are not industrial parks or residential complexes.

For each type of zone, a variable is defined to show, by percentage, the degree to which each company belongs to that type of zone so that the sum of the four variables for each company always gives the value 1 (100%).

If we admit that the size of the company and its operating area influence its technology, it seems reasonable to suppose that the clusters generated with these variables contain units that share a relatively homogeneous technology. Regarding the size of the company, the largest ones operate at higher voltage levels, normally feeding from the transmission network, which makes them develop more complex electrical transformation (substations), control and protection systems. This fact allows them to deliver greater quantities of energy over greater distances. On the other hand, the urban/rural character of the distributor affects the deployment of underground/overhead installations; urban firms utilize mainly underground network, which causes their costs to multiply by ten. Therefore, our working hypothesis is that the clusters composed of urban and large companies are those that present a more complex and expensive technology.

Due to the different nature of the size and zone attributes, we have chosen to generate a cluster of distributors following two steps. In the first step, two separate k-means clustering processes are carried out, while in the second step, the two clusters obtained in the first stage are combined to generate biclusters –i.e., clusters in both dimensions, size, and area. For the first step, the first cluster is using five variables of size to generate 4 clusters: large firms, medium firms, small firms, and very small firms. The second cluster is using four operating zone variables to generate another 4 clusters: mainly urban, mainly semi-urban, mainly rural-concentrated, and mainly rural-dispersed.

Importantly, the number of clusters by size and zone has not been selected exogenously but endogenously. When the optimal number of clusters is unknown, Makles (2012) proposes a method whereby several k-means solutions with different numbers of groups k ($k = 1,\ldots, k-1, k,\ldots,K$) are computed and compared. To find the clustering with the optimal number of groups k^*, this author searches for a fold in the curve that describes the evolution in k of the *within sum of squares* (*WSS*) or its logarithm. For each variable used in the clustering process and for each number of partitions k, the squared sum of the difference between each value of the variable and the average value of the variable in the cluster to which the value belongs can be obtained; *WSS* is just the total sum of all those sums of squares. Other criteria for detecting the optimal number of clusters are the η^2 coefficient and the proportional reduction of error (*PRE*) coefficient (Schwarz, 2008):

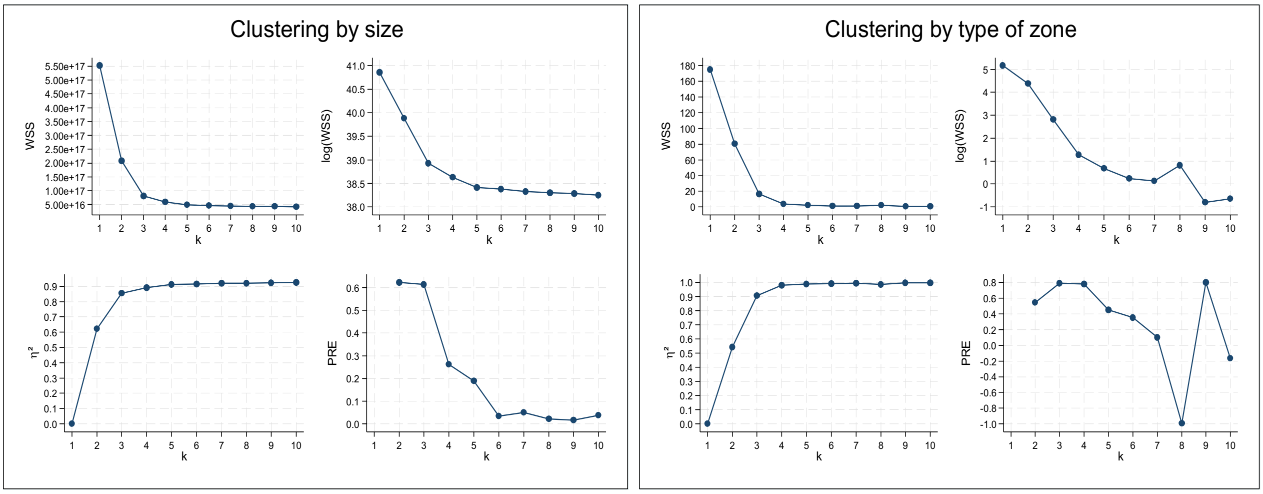
$$\eta_k^2 = \frac{WSS(1) - WSS(k)}{WSS(1)} = \frac{TSS - WSS(k)}{TSS} \qquad \forall k \in K \tag{6}$$

$$PRE_k = \frac{WSS(k-1) - WSS(k)}{WSS(k-1)} \qquad \forall k \geq 2 \tag{7}$$

WSS(k) is the *WSS* for cluster solution k (where $k = 1, \ldots, k–1, k, \ldots, K$) and η_k^2 measures the proportional reduction of the *WSS* for each cluster solution k compared with the total sum of squares (*TSS*), the latter being the *WSS* for cluster solution $k = 1$ (i.e., nonclustered data). In contrast, PRE_k illustrates the proportional reduction of the *WSS* for cluster solution k compared with the previous solution $k - 1$.

Figure 1 shows the four indicators described for the two k-means clusters, the one by size and the one by zone; in both cases, values of k between 1 and 10 have been tested. The results point to $k^* = 4$ as the optimal solution in both clusters, since the respective functions *WSS*, log(*WSS*), and η^2 becomes flat from that value; you cannot reduce much more the *within sum of squares* by using values of k greater than 4. The function PRE_k seems to indicate 3 and 4 optimal groups in the clusters by size and zone, respectively; for higher values of k, this indicator experiences a significant fall. Finally, considering the four indicators together, we have decided to consider four groups of distributors in both k-means clusters.

Figure 1. *WSS*, log(*WSS*), η^2, and *PRE* for 'k=1 to 10' cluster solutions.



Once the two k-means clusters (by size and zone) have been defined, the next grouping step to identify homogeneous groups of distributors is to combine both clusters. Proceeding in this way, we generate 16 possible partitions or biclusters, although the analyzed distributors have been located in only ten of those partitions. Furthermore, in order to guarantee a sufficient number of DMUs inside each bicluster, some of these ten partitions have been merged into one single bicluster; the merged groups are relatively close in terms of size and type of zone (i.e., they are contiguous biclusters). After all this grouping process, the 231 distributors submitted to the biclustering process are grouped into six different biclusters (or, simply, clusters). To complete the classification process, we have added one more group to these six clusters, which is formed by the five main distributors in Spain (Endesa, Iberdrola, Unión Fenosa, HidroCantábrico, and Viesgo). These companies are very much larger than the other units and, therefore, are considered directly as a separate group.

At the end of the whole grouping process, the firms have been grouped into seven groups or clusters (see Table 2 and Figure 2), namely: (1) very small and mainly urban units (32 units), (2) very small and mainly semi-urban units (82 units), (3) very small or small and rural-concentrated or rural-dispersed units (111 units), (4) small or medium and mainly urban units (15 units), (5) small or medium and mainly semi-urban units (26 units), (6) large and mainly urban units (5 units), and (7) very large units (5 units) –cluster seven is not depicted in Figure 2 because it would minimize the other groups.

Table 2. Seven clusters of distributors.

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="4">Cluster by type of zone</th><th></th></tr>
<tr><th>Mainly urban</th><th>Mainly semi-urban</th><th>Rural-concentrated</th><th>Rural-dispersed</th><th>Total</th></tr>
<tr><th rowspan="5">Cluster by size</th><th>Very small</th><td>25</td><td>73</td><td>92</td><td>8</td><td>198</td></tr>
<tr><th>Small</th><td>5</td><td>16</td><td>0</td><td>0</td><td>21</td></tr>
<tr><th>Medium</th><td>5</td><td>2</td><td>0</td><td>0</td><td>7</td></tr>
<tr><th>Large</th><td>5</td><td>0</td><td>0</td><td>0</td><td>5</td></tr>
<tr><th>Very Large</th><td colspan="4">5</td><td>5</td></tr>
<tr><th></th><th>Total</th><td>45</td><td>91</td><td>92</td><td>8</td><td>236</td></tr>
</table>

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="4">Cluster by type of zone</th></tr>
<tr><th>Mainly urban</th><th>Mainly semi-urban</th><th>Rural-concentrated</th><th>Rural-dispersed</th></tr>
<tr><th rowspan="5">Cluster by size</th><th>Very small</th><td>Cluster 1 (25)</td><td>Cluster 2 (73)</td><td colspan="2">Cluster 3 (100)</td></tr>
<tr><th>Small</th><td rowspan="2">Cluster 4 (10)</td><td rowspan="2">Cluster 5 (18)</td><td colspan="2" rowspan="2"></td></tr>
<tr><th>Medium</th></tr>
<tr><th>Large</th><td>Cluster 6 (5)</td><td colspan="3"></td></tr>
<tr><th>Very Large</th><td colspan="4">Cluster 7 (5)</td></tr>
</table>

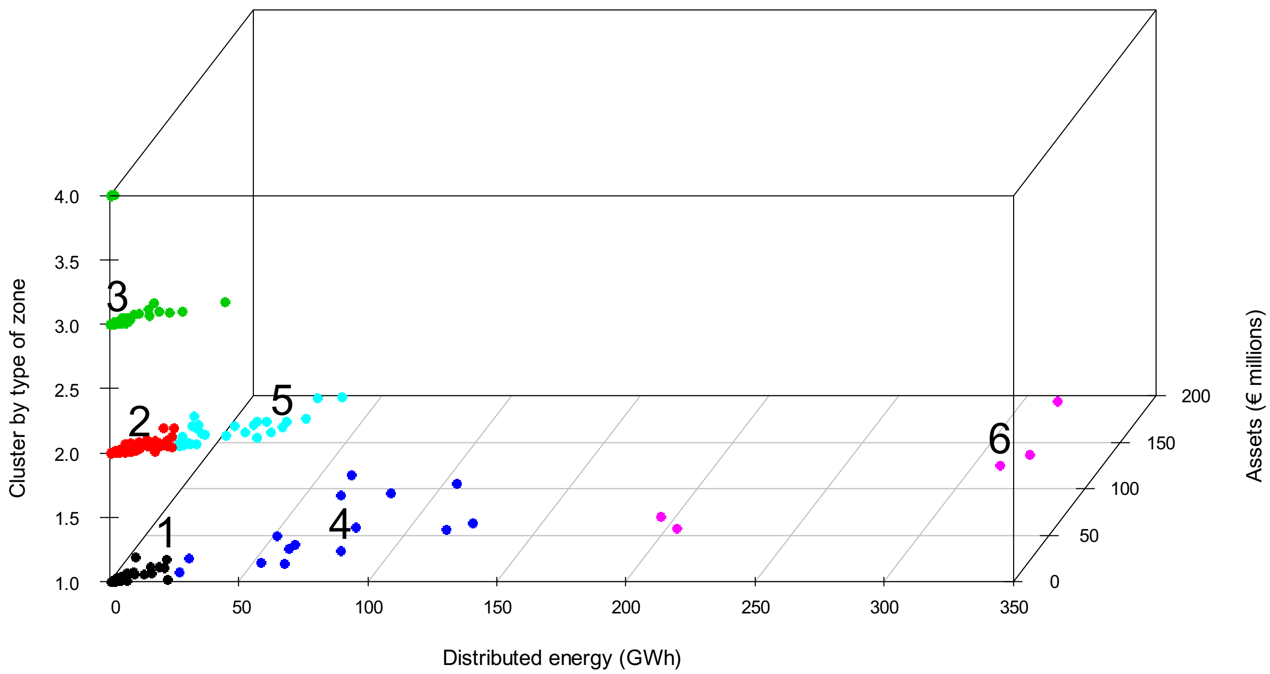


Figure 2. 3D rendering of distributor groups.

We apply a one-way analysis of variance (ANOVA) to test for differences among the means of the unit remuneration variable (€ per MWh) across clusters. The between-group sum of squares for the simple model 'unit remuneration by cluster' represents the 18.7% of the total sum of squares. The corresponding F statistic is 8.79 and has a p-value very close to zero, which means that the model appears to be significant, or in other words, that we can reject the null hypothesis of equal means across clusters.

Table 3 shows descriptive statistics for the entire sample and by cluster of the variables involved in the DEA analysis.

Table 3. Descriptive statistics by cluster in 2016.

Variable	Cluster	Obs.	Mean	Std. Dev.	Min	Max
Remuneration per distributed energy (€ / MWh)	All	236	137.5	91.8	18.2	736.1
	1. Very small - Mainly urban	25	162.3	111.9	58.1	637.0
	2. Very small - Mainly semi-urban	73	118.3	56.3	51.9	308.5
	3. Very small - Mainly rural	100	172.2	103.5	54.5	736.1
	4. Small-medium - Mainly urban	10	90.0	32.0	45.8	133.4
	5. Small-medium - Mainly semi-urban	18	72.6	23.9	35.6	114.8
	6. Large - Mainly Urban	5	44.9	15.8	28.0	61.1
	7. Very large	5	22.1	4.3	18.2	29.5
Remuneration per P.o.S. (€ / unit)	All	236	454.8	1,218.1	152.9	17,371.1
	1. Very small - Mainly urban	25	1,370.6	3,626.5	193.0	17,371.1
	2. Very small - Mainly semi-urban	73	321.6	102.9	181.4	666.1
	3. Very small - Mainly rural	100	380.5	287.9	179.6	2,550.3
	4. Small-medium - Mainly urban	10	301.9	80.6	177.4	396.8
	5. Small-medium - Mainly semi-urban	18	332.0	122.3	194.5	676.6
	6. Large - Mainly Urban	5	301.9	75.2	193.0	401.3
	7. Very large	5	208.6	53.7	152.9	277.1
Remuneration per Assets. (€ / €)	All	236	0.154	0.078	0.042	0.576
	1. Very small - Mainly urban	25	0.130	0.065	0.042	0.346
	2. Very small - Mainly semi-urban	73	0.148	0.078	0.048	0.576
	3. Very small - Mainly rural	100	0.182	0.082	0.058	0.425
	4. Small-medium - Mainly urban	10	0.107	0.028	0.064	0.154
	5. Small-medium - Mainly semi-urban	18	0.113	0.030	0.052	0.184
	6. Large - Mainly Urban	5	0.108	0.028	0.069	0.142
	7. Very large	5	0.076	0.015	0.061	0.099
Distributed energy per P.o.S. (kWh / unit)	All	236	3,513.1	4,657.7	320.3	67,847.3
	1. Very small - Mainly urban	25	6,082.2	13,080.2	956.0	67,847.3
	2. Very small - Mainly semi-urban	73	2,997.8	860.3	916.2	5,368.9
	3. Very small - Mainly rural	100	2,512.9	1,465.7	320.3	12,583.5
	4. Small-medium - Mainly urban	10	3,480.5	531.6	2,809.2	4,146.1
	5. Small-medium - Mainly semi-urban	18	4,798.1	1,584.5	2,305.0	8,844.0
	6. Large - Mainly Urban	5	7,498.5	3,867.7	4,867.9	14,316.6
	7. Very large	5	9,649.8	3,122.5	7,695.8	15,184.3
TIEPI (Hours)	All	236	1.47	1.1	0.1	6.7
	1. Very small - Mainly urban	25	0.58	0.2	0.3	1.0
	2. Very small - Mainly semi-urban	73	1.18	0.5	0.5	2.7
	3. Very small - Mainly rural	100	2.09	1.4	0.1	6.7
	4. Small-medium - Mainly urban	10	0.62	0.2	0.3	1.0
	5. Small-medium - Mainly semi-urban	18	1.23	0.5	0.5	2.5
	6. Large - Mainly Urban	5	0.97	0.5	0.6	1.7
	7. Very large	5	0.46	0.1	0.3	0.6

At least three stylized facts can be observed in the table. On the one hand, the remuneration per distributed energy and the one per fixed assets decreases drastically with size and increases from mainly urban to mainly rural zones. For example, in terms of remuneration per distributed energy, the highest-paid group, cluster three (smallest companies with rural character and lowest level of assets on average), enjoys, on average, a unitary payment 3.8 and 7.8 times higher than that received by clusters six (large mainly urban companies) and seven (very large companies), respectively. On the other hand, the remuneration per connection point is relatively high in the case of cluster 1 (very small, mainly urban companies), being more than four times higher than the unitary remuneration of the groups from two to six (except for cluster three, for whom the ratio is somewhat less: 3.6), and more than six times higher if the comparison is made with cluster seven (very large companies). Finally, the quality of service is significantly lower (i.e., higher TIEPI) in rural zones and also in smaller sizes; for example, the lowest quality group, which is one of very small companies with rural character (cluster 3), has on average a TIEPI 3.6 and 4.6 times higher than that exhibited by clusters one (very small mainly urban companies) and seven (very large companies), respectively.

6. DEA meta-frontier analysis.

This section builds the meta-frontier of the complete set of distributors and the local frontiers of the different clusters, solving a meta-frontier DEA optimization problem with two inputs and three outputs. The input variables are the remuneration of each firm j (REM_j), which is discretionary in the model, and the level (in Euros) of fixed assets ($ASSETS_j$, non-discretionary). The output variables are the number of connection points (CLI_j, non-discretionary), the distributed energy (DE_j, non-discretionary), and an individual indicator of the quality of service (QI_j), which is defined later in this section. The meta-frontier DEA approach, which does not necessarily require the aforementioned separability condition, has the advantage that allows the evaluation of two efficiency levels: *global* efficiency, which supposes that each DMU is compared with all the units in the sample –i.e., it is assumed that they all have access to the same technology; and *cluster* efficiency, which supposes that each DMU is compared only with those units that belong to their own cluster, inside of which all the firms operate with relatively similar contextual conditions and, therefore, with a common technology. The two models resolved are:

DEA Meta-frontier	*DEA Cluster-frontier (k clusters)*
$$\begin{aligned} &Min \quad \theta_0 - \epsilon s_0^+ \\ &s.t. \\ &\sum_{j=1}^{n} \lambda_j REM_j \leq \theta_0 REM_0 \\ &\sum_{j=1}^{n} \lambda_j ASSETS_j \leq ASSETS_0 \\ &\sum_{j=1}^{n} \lambda_j CLI_j \geq CLI_0 \\ &\sum_{j=1}^{n} \lambda_j DE_j \geq DE_0 \\ &\sum_{j=1}^{n} \lambda_j QI_j = QI_0 + s_0^+ \\ &\sum_{j=1}^{n} \lambda_j = 1 \\ &\lambda_j \geq 0 \qquad \forall j = 1, \dots, n \\ &\theta_0 \quad free,\ s_0^+ \geq 0 \end{aligned} \tag{8}$$	$$\begin{aligned} &Min \quad \theta_0^k - \epsilon s_0^{k+} \\ &s.t. \\ &\sum_{j=1}^{n} \lambda_j^k REM_j^k \leq \theta_0^k REM_0^k \\ &\sum_{j=1}^{n} \lambda_j^k ASSETS_j^k \leq ASSETS_0^k \\ &\sum_{j=1}^{n} \lambda_j^k CLI_j^k \geq CLI_0^k \\ &\sum_{j=1}^{n} \lambda_j^k DE_j^k \geq DE_0^k \\ &\sum_{j=1}^{n} \lambda_j^k QI_j^k = QI_0^k + s_0^{k+} \\ &\sum_{j=1}^{n} \lambda_j^k = 1 \\ &\lambda_j^k \geq 0 \qquad \forall j = 1, \dots, n \\ &\theta_0^k \quad free, \quad s_0^{k+} \geq 0 \end{aligned} \tag{9}$$

Note: the different parameters of the models have been explained in Section 3.

Observe that, in essence, there are two ways to develop the meta-frontier, convex and non-convex. Some recent literature argues that assuming the convex meta-frontier may lead to problematic interpretations of benchmarks and could underestimate the efficiency measures obtained (Afsharian and Podinovski 2018; Kerstens *et al.* 2019; Asmild, 2015). However, in our case, the sample of electricity distributors is not exhaustive; hence, some DMUs have not been represented. The consideration of a non-convex meta-frontier potentially could not include the combination of inputs and outputs of those missing electricity distributors, hence a convex meta-frontier is conceivable in our case (O'Donnell *et al*., 2008).

With the results obtained in both models, Figure 3 represents the current unit remuneration (€/MWh), the global-efficient unit remuneration, and the cluster-efficient unit remuneration of each distributor when the DMUs are sorted by cluster and current unit remuneration (from lowest to highest). As we can observe, the global-efficient unit remuneration envelops the current and the cluster unit remunerations; it has a mean (75.9) and a standard deviation (60.8) significantly lower than the mean and standard deviation of the observed unit remuneration (see Table 2). In our opinion, the values of this global-efficient unit remuneration constitute a theoretical benchmark rather than a practical one, since they imply that companies could change (at least, in the long term) their technology, which is complicated in our sample given the fixed contextual conditions. As for the cluster-efficient unit remuneration (with mean = 92.1 and standard deviation = 60.9), it represents the efficient values achievable by the different units in the short term (given a particular technology). This latter unitary revenue constitutes, in our model, the Regulator's remuneration target: those firms that are relatively far from their cluster-efficient value are inefficient units, according to the Regulator. Finally, another fact to highlight in the figure is that the companies in clusters 6 and 7 (the ten largest companies) have real and efficient values lower than those of the rest of the clusters, i.e., they are less expensive for society. Moreover, these companies are relatively efficient because they are close to or bordering their respective frontiers.

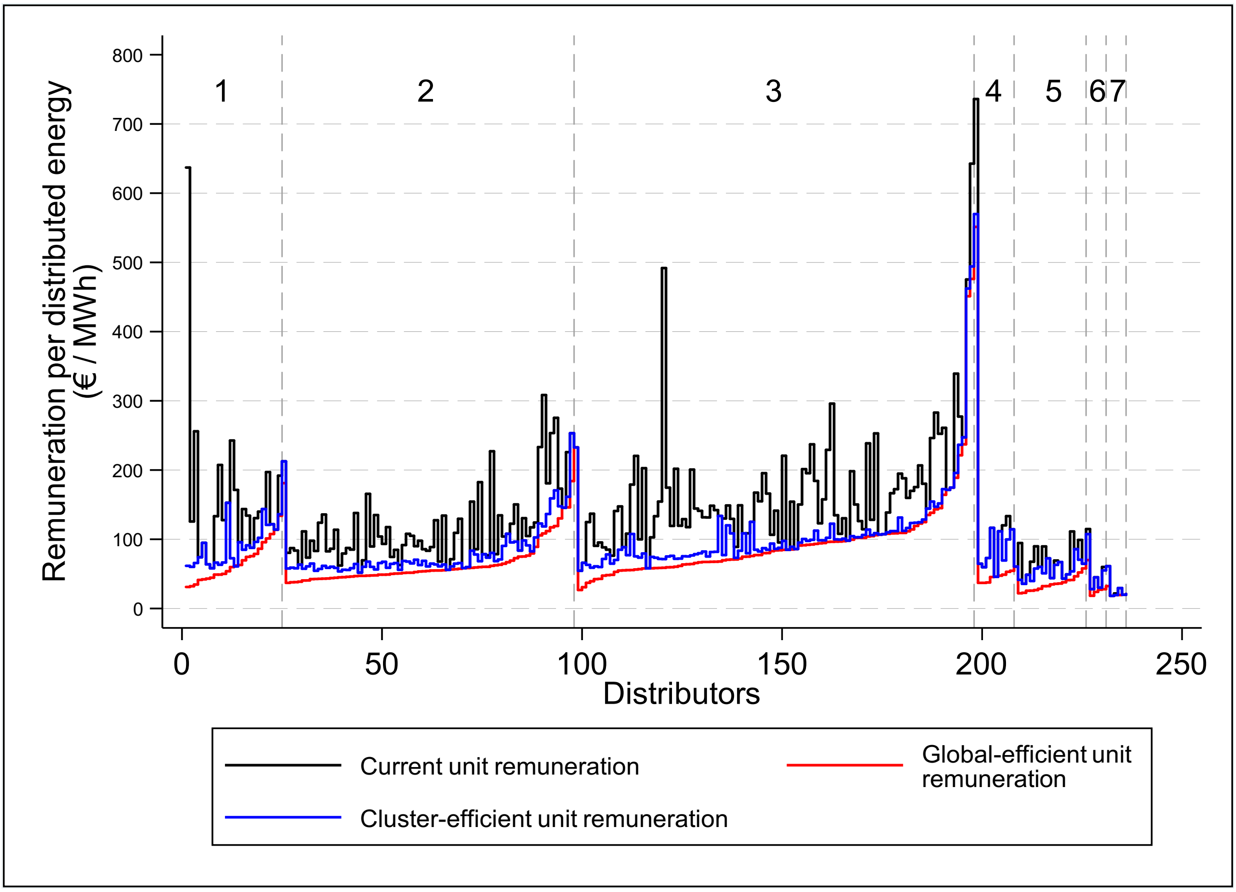
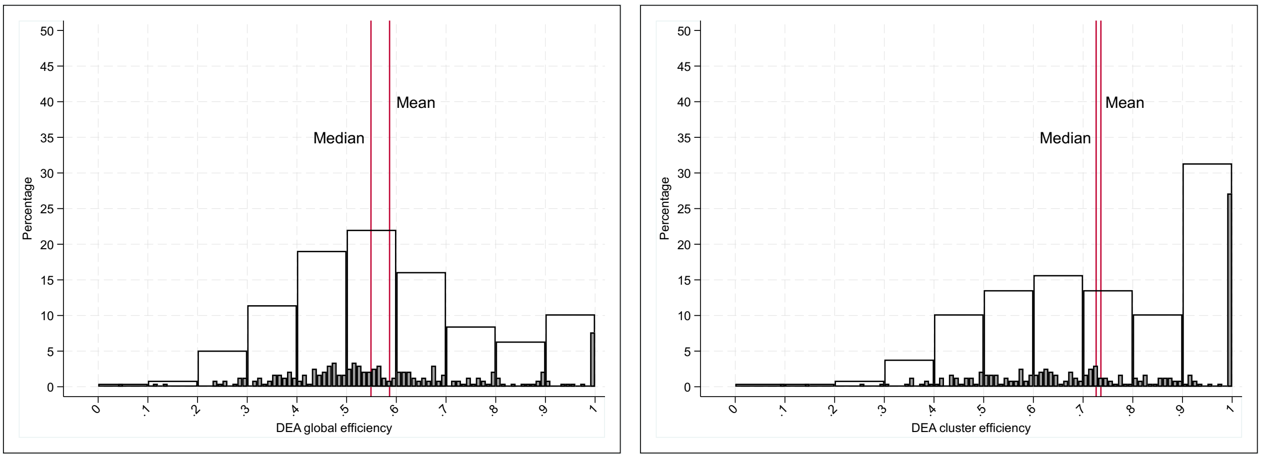


Figure 3. Current unit remuneration vs. efficient unit remuneration by cluster.

Figure 4 depicts the histograms by the percentage of the efficiency scores of the DMUs with respect to the meta-frontier, graph 4(a), and to their respective local frontiers, graph 4(b). The mean and the median are below 0.6 in the meta-frontier distribution (mean=0.59 and median=0.55), while they are close to 0.75 in the case of the cluster distribution (mean=0.74 and median=0.73). We have performed a nonparametric *K*-sample contrast to test for efficiency differences among clusters. This contrast tests (for unmatched data) whether *K* different samples are likely to derive from the same population; some researchers interpret this test as comparing the medians among the *K* possible populations. In our case, the null hypothesis is that the intra-cluster efficiency scores of the *K*=7 clusters were drawn from populations with the same median. The *p*-value for Pearson's χ^2 test and the value of Fisher's exact *p* are very close to 0, which allows the rejection of the null hypothesis that there is no difference between the efficiency scores across the clusters. The efficiency results show that the efficient distributors do not reach 8% of the total units in the meta-frontier model (7.6%), while this percentage is higher than 25 % in the cluster model (27.1%). In Spain, there is further scope for the electricity distribution sector to improve efficiency.



4(a) Meta-frontier 4(b) Cluster frontier

Figure 4. Efficiency scores in the meta-frontier model and the cluster model.

We adopt an economic approach similar to that of Arcos *et al.* (2017). The main purpose of both papers is to assess whether the amount of income that the distribution companies receive is adequate for the quality and quantity of energy delivered with a particular capital structure. Hence, the standpoint of the Regulator (and of society) is adopted rather than that of the individual firm. The Regulator considers remuneration as an input of the electricity distribution system, and it should be sufficient to provide a given amount of energy with a certain level of quality. In both analyses, the DEA models use as a discretional input the remuneration obtained by each distribution company and, as a non-discretional input, the value of their fixed assets (in Euros), which is associated with the voltage level and the network segment in which each private company operates. Both models also use as non-discretional outputs, the number of connection points, and the energy delivered for each unit. However, there are at least two key differences between the two approaches. On the one hand, a cluster-based meta-frontier model is calculated instead of the ordinary DEA model with constant or variable returns to scale. On the other hand, the quality of service is not measured through the undesirable output *ENS* (energy not supplied), but through a TIEPI-based indicator defined as the subtraction: the “average of TIEPI corresponding to the periods n-3, n-4 and n-5” minus “average of TIEPI corresponding to periods n-2, n-3 and n-4.” Under Spanish regulation, a positive (negative) indicator generates a stimulus (penalty) for the company. Therefore, this component is treated as a discretionary output within the model; in our opinion, the problem of this incentive mechanism is that the effect on the incentive of a permanent improvement is only temporary.

In those countries where electricity distribution is a regulated activity, the national Regulator determines the remuneration of each company. In Spain, these payments are calculated and settled by the "*Comisión Nacional de los Mercados y la Competencia*" (CNMC). The Spanish regulatory regime is based on incentives and benchmarking. Specifically, the Regulator establishes an incentive component for quality improvement and loss reduction along with a rate of return for the firm, with the objective that revenues have to cover operating and capital costs as well as a suitable return on capital. To determine these retributive factors, the Regulator has developed a frontier theoretical model that takes into account the size of each distributor in the context of a unique common frontier, so, in that sense, the official model resembles more a traditional DEA model with variable returns to scale than a meta-frontier DEA model. By calculating a meta-frontier model, we postulate an alternative to the official remunerative method currently employed by the national Regulator.

Table 4 shows some aggregated results from the meta-frontier model calculated. The measure of the overall efficiency of the distribution system in terms of remuneration ($\bar{E}$) is calculated as the ratio between the total efficient income proposed by the model (R^*) and the one observed in the actual data (R). This measure is equivalent to the weighted average of the ratio which relates the virtual (efficient) remuneration proposed by the model for each firm j (r_j^*) to their actual remuneration (r_j):

$$\bar{E} = \frac{R^*}{R} = \frac{\sum_{j=1}^{n} r_j^*}{\sum_{j=1}^{n} r_j} = \sum_{j=1}^{n} \frac{r_j}{\sum_{j=1}^{n} r_j} \frac{r_j^*}{r_j} \quad (10)$$

The individual DEA remuneration r_j^* can be either the global-efficient unit remuneration or the cluster-efficient unit remuneration. The savings of resources for the systems are given by: $\bar{E} - 1 = \frac{R^*}{R} - 1 = \frac{R^* - R}{R}$.

Table 4. Remunerative efficiency of electrical distribution in Spain.

<table>
<tr><th>Clusters</th><th>Within-cluster efficiency (%)</th><th>Savings for the system (%)</th><th>Savings for the system (€ millions)</th><th>Overall cluster efficiency</th><th>Overall meta-frontier efficency</th></tr>
<tr><td>1. Very small - Mainly urban</td><td>67.4%</td><td>32.6%</td><td>4.7</td><td rowspan="7">97.6%
(2.4%)</td><td rowspan="7">95.0%
(5%)</td></tr>
<tr><td>2. Very small - Mainly semi-urban</td><td>72.0%</td><td>28.0%</td><td>14.7</td></tr>
<tr><td>3. Very small - Mainly rural</td><td>68.3%</td><td>31.7%</td><td>9.4</td></tr>
<tr><td>4. Small-medium - Mainly urban</td><td>90.1%</td><td>9.9%</td><td>5.9</td></tr>
<tr><td>5. Small-medium - Mainly semi-urban</td><td>83.1%</td><td>16.9%</td><td>8.5</td></tr>
<tr><td>6. Large - Mainly Urban</td><td>97.5%</td><td>2.5%</td><td>1.5</td></tr>
<tr><td>7. Very large</td><td>98.4%</td><td>1.6%</td><td>73.6</td></tr>
<tr><td></td><td></td><td></td><td>118.3</td><td>118.3
(€ millions)</td><td>252.5
(€ millions)</td></tr>
</table>

The results obtained show that the system as a whole is not fully efficient even when the cluster frontiers are taken as reference. Thus, the overall efficiency is 97.6% when each distributor is compared to the frontier of its own cluster, and it is 95% when the distributors are looking at the meta-frontier. That is, the annual savings for the units in the sample would vary between 118.3 and 252.5 million € in the cases of cluster-frontier and meta-frontier, respectively; extrapolating these figures to the total number of distributors in Spain (347 companies), the annual savings would amount to 174 M€ and 371 M€, respectively. When the different clusters are compared to each other, it is observed that the larger groups show a greater degree of efficiency, the clusters of very small companies being the most inefficient; very small clusters, 1, 2, and 3, could save more than 28 million Euros for the system if they behaved efficiently.

An analogous analysis to that of remuneration can be made with the TIEPI-based quality component (also discretionary in the DEA model). Table 5 shows the inefficiency score in each cluster and the full system, as well as the average value of the quality indicator in each cluster.

Table 5. Quality efficiency of electrical distribution in Spain.

Clusters	Cluster inefficiency	Average TIEPI-based component by cluster
1. Very small - Mainly urban	1.02	0.39
2. Very small - Mainly semi-urban	3.44	0.10
3. Very small - Mainly rural	2.63	0.24
4. Small-medium - Mainly urban	1.01	0.14
5. Small-medium - Mainly semi-urban	1.65	0.25
6. Large - Mainly Urban	1.10	0.35
7. Very large	1.17	0.04
Complete system	2.23 - 2.27	

As can be seen in the table, the quality efficiency appears more closely associated with the type of zone than to the size of the company, the companies that operate in semi-urban or rural areas being the most inefficient in quality terms. For instance, cluster 2 (very small – mainly semi-urban) would have a 3.4 times greater TIEPI-based component if all its companies were efficient within the cluster. This cluster is especially striking because its average component is relatively small (as also happens with the cluster of the largest companies); this could be indicative of how difficult it is for their companies to achieve quality improvements. Finally, looking at the system as a whole, it can be observed that the quality of the whole system could be multiplied by more than 2.2 if all the companies were efficient in their corresponding cluster. As we saw before for remuneration, in Spain, there is also scope for the electricity distribution sector to improve in quality.

Our empirical analysis concludes with two multiple linear regressions that try to measure the effect on the current and the cluster-efficient remuneration of three kinds of attributes: company size, operation zone, and quality of service. In turn, the size attribute is controlled by three variables, which are the level of fixed assets (in Euros), the number of connection points, and the distributed energy (MWh). The zone variable is a dummy (0 or 1) that differentiates between mainly urban operation area (0) and mainly rural operation area (1). Finally, the quality variable is de TIEPI-based component previously described in this section. The two dependent variables and the three size variables are expressed in logarithms (the estimated coefficients of size variables represent elasticities), which allow us to capture possible nonlinearities in the relationship between remuneration and size. The regression of the cluster-efficient remuneration can present correlation problems because deterministic DEA models generate correlation patterns among the estimated efficiency scores, and therefore among the efficient inputs or outputs obtained from them –on this econometric problem, see, for example, Simar and Wilson (2007). This problem can be partially mitigated under the meta-frontier approach, since the correlation between units is limited to the units belonging to each cluster-frontier –at least, at the serial correlation level, which is the most apparent correlation. However, for a more robust estimate, we have estimated the variance-covariance matrix corresponding to the parameter estimates (and, therefore, to their confidence intervals) using a cluster-based bootstrap procedure in which the sample was drawn during each replication (200 replications) is a bootstrap sample of clusters. The estimation results are shown in Table 6.

Table 6. Multiple linear regressions of the current remuneration and the cluster-efficient remuneration.

Model for the current remuneration (log)						
	Coef.	**Std. Err.**	**t**	**p>|t|**	**[95% Conf. Interval]**	
Distributed energy (MWh) (log)	0.18***	0.031	5.76	0.000	0.119	0.242
Points of supply (log)	0.24***	0.03	8.21	0.000	0.185	0.301
Fixed assets (€) (log)	0.47***	0.022	21.74	0.000	0.429	0.514
TIEPI-based component	0.014	0.01	1.38	0.168	-0.006	0.033
Mainly rural (dummy)	0.071*	0.032	2.2	0.029	0.007	0.135
Constant	-11.13***	0.187	-59.62	0.000	-11.498	-10.762
Number of obs. = 236; R^2 = 98.5%; Adj. R^2 = 98.4%; Root MSE = 0.2075; F(5, 230) = 2925.5 (Prob > F = 0.00)						
Model for the cluster-efficient remuneration (log). Bootstrap sampling and estimation.						
Replications = 200	**Observed Coef.**	**Bootstrap Std. Err.**	**z**	**p>|z|**	**Normal-based [95% Conf. Interval]**	
Distributed energy (MWh) (log)	0.28***	0.059	4.85	0.000	0.169	0.399
Points of supply (log)	0.53***	0.094	5.65	0.000	0.345	0.712
Fixed assets (€) (log)	0.13***	0.018	6.97	0.000	0.091	0.163
TIEPI-based component	0.035***	0.008	4.44	0.000	0.020	0.051
Mainly rural (dummy)	-0.014	0.07	-0.2	0.842	-0.150	0.123
Constant	-9.21***	0.153	-60.13	0.000	-9.512	-8.911
Number of obs. = 236; R^2 = 98.6%; Adj. R^2 = 98.5%; Root MSE = 0.2091; Wald $chi^2(5)$ = 15385.7 (Prob > chi^2 = 0.00)						

Note: Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Once estimated, both models have a high coefficient of determination (R^2), which means that the two of them fit well to the sample. Moreover, in both models, most of the coefficients are significant with a 95% confidence level. In the model that explains the current remuneration, the remunerative elasticities for distributed energy, the number of connection points, and the level of fixed assets are less than one, being the level of assets the one with a higher coefficient (0.47) –having 1% more assets increases the distributor's revenue by approximately 0.5% (all other factors being equal). On the other hand, it is worrying that the quality component does not seem to have a significant effect on remuneration. Finally, belonging to a rural area shows a positive effect on the estimation, the remuneration increases by 7%. When the observed remuneration is replaced by the cluster-efficient remuneration as the dependent variable of the model, some interesting differences appear between both estimates. Specifically, if we assume that all units are efficient within their respective clusters, the estimated coefficients of the (output) variables connection points and distributed energy increase, and the coefficient of the (input) variable fixed assets is reduced. For instance, owning 1% more clients (points of supply) increases the optimal remuneration by 0.53% (not by 0.24%); and having 1% more assets increases the optimal remuneration by 0.13% (not by 0.47%). Likewise, a unitary increase in the TIEPI-based component should increase the optimal remuneration of the distributor by approximately 4%, while belonging to a rural area should not produce, in the efficient system, an extra-payment in the optimal remuneration received. These different results between estimates might suggest that the current compensation system in Spain is failing to guide the distribution companies to their respective intra-cluster frontiers.

7. Conclusion and Policy Implications.

We present a benchmarking framework that takes into account the heterogeneity of firms and their operating environment. By combining *k*-means clustering and DEA meta-frontier techniques, we make the efficiency targets of each firm more realistic, since they are established taking into account the contextual conditions of the firm in terms of scale and operational zone. This 2-step procedure shows high flexibility due to the independence of the two implemented stages, i.e., clustering and production efficiency analysis can be optimized separately. Other clustering techniques might be inserted in our 2-step methodological approach. However, the *k*-means clustering works well when the shape of clusters tends to be hyper-spherical, and the clear differentiation by size and operation area of Spanish distributors seems to be compatible with this scenario. Equally, other efficiency measurement techniques could be used, but the DEA meta-frontier model allows a flexible (nonparametric) adjustment of the different production technologies. Its use in the literature to analyze the electrical distribution sector is relatively small compared to that of stochastic frontier models: to some extent, we contribute to filling a gap in the literature.

We apply our methodology to the Spanish electrical distribution industry. In Spain, the distribution activity represents 25% of total system costs and consists of 347 fully regulated companies, which operate independently and with an exclusive social object. These companies are very different in terms of size and operational conditions; five ‘very large’ utilities, which feed from the transmission and have, on average, five million points of supply (P.o.S.), are accompanied by a set of 342 firms, which feed from lower voltage levels and have, on average, less than 5,000 P.o.S. These last companies have very different sizes (large, medium, small and very small units) and operate in very different geographical areas (urban, semi-urban, rural-concentrated and rural-dispersed zones). These differences imply that not all companies face the same production possibility set (the separability condition does not apply), so a meta-frontier DEA model is appropriated to measure their efficiency. The central purpose of our model is to assess whether the amount of income that the DisCo receive (income that represents a social cost) is adequate, within its cluster, for the quality and quantity of energy delivered. Hence, the standpoint of the Regulator (and of society) is adopted rather than that of the individual firm. Our hypothesis is that, although the operational conditions of the DisCos are different, the much higher average costs of the smaller firms are hard to justify.

Our sample is composed of 236 distributors (including the five largest firms), and the analysis is carried out with input and output data from the year 2016. The static nature of our analysis (due to the unavailability of time series data) advises some caution when drawing conclusions from the results and providing policy guidance. The results obtained show that the Spanish electricity system as a whole is not fully efficient, even when the cluster frontiers (not the meta-frontier) are taken as reference. Thus, the overall efficiency is 97.6% when each distributor is compared to the frontier of its own cluster, and it is 95% when the distributors are looking at the meta-frontier. The annual savings would be 174 M€ if all the units were cluster-efficient, and the quality service indicator could be multiplied by more than 2.2. Therefore, in Spain, there is also scope for the electricity distribution industry to improve efficiency and quality. Finally, our study suggests that the current compensation system in Spain is failing to guide the distribution companies to their respective intra-cluster frontiers.

Not having the full population of Spanish distribution companies, nor their real production costs (or their levels of production factors) are, along with the impossibility of obtaining a temporary data panel, the main limitations of our study and, at the same time, the main challenges for our future research. For instance, by extending the analyzed period, it would be possible to study the dynamic evolution of the meta-frontier and the cluster frontiers, as well as the relative position of the different units within their respective clusters. Other avenues for future research would be to evaluate the convexity (or non-convexity) of the meta-frontier or to test alternative configurations of the clustering and efficiency analysis methods when they are used in combination for benchmarking purposes.

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