Regulation of Electricity Distribution Companies - DEA with Separable Costs

By

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Abstract

The Norwegian model for regulating electricity transmission and distribution consists of a revenue cap, with additional limits on maximum and minimum returns, and is also a performance based regulation, since DEA (data envelopment analysis) is used to evaluate the efficiency of the individual companies, and to determine individual efficiency requirements. In the 5 year regulation periods, intra-period revenue-updates are based on external factors like KPI, increases in national loads etc. Inter-period updates are based on average historical costs for each company, and the results from the DEA model are used to make a yearly reduction in the allowed revenues for the individual companies. Our concern has been the relevance of the results of the DEA model, i.e. how companies can learn from the outputs of the "black-box" model on where and how to improve, and the information value to the regulator. The starting point is a suggestion for a more norm based regulation, where a cost model separating customer-related and network-related costs applies. There are clear indications that such a separation of the cost base is valid and possible, and that it could and perhaps should be used in the regulation of the companies in the best possible way. In the paper, the present DEA model is described, and we study the effects of assuming separable costs, and what happens with two separate analyses, or if everything is combined into a single model/measurement. Mathematical results are provided for special cases, along with results from simulation experiments.

Keywords: Regulation, Electricity Distribution, Data Envelopment Analysis (DEA)

1. Introduction

When the Norwegian electricity market was deregulated in 1992, it implied an unbundling of generation and transmission/distribution, and the operations of the grid companies have remained regulated, since they are operating in a monopoly market. Various schemes have been used, starting

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with a period of Rate-of-Return regulation, which later (since 1997) has been changed to what can be regarded as a combination of an incentive-based and a performance-based regulation. Moreover, maximum and minimum returns on capital are determined, and these constitute additional constraints on the revenues.

The starting point when introducing the revenue cap regulation in 1997, was to give economic incentives for operating and developing the grids efficiently, and this was to be achieved by decoupling the revenues of the grid companies from accounted costs. To a certain extent, the regulation scheme that followed attained this goal, as the yearly updates of the revenues *within* the regulation periods (presently covering a period of 5 years) are based on factors like inflation, changes in interest-rates and energy-prices (applies to energy losses), general and individual efficiency-requirements, and adjustment-factors based on new customers / changes in energy consumption. These are all factors independent of the companies' accounted costs within the present regulation period.

However, since the initial revenues at the start of the regulation periods (1997 and 2002 so far) have been determined based on average actual costs in the previous regulation period, the regulation model has a considerable element of cost-plus regulation. For the grid companies this means that there may be a trade-off between on the one hand increasing the efficiency and attaining better results today, and on the other hand, get a lower revenue cap for the next regulation period. Another effect is that the regulation may prevent an efficient organization of the activities performed, i.e. an implementation of the tasks that is in accordance with best business practices, for instance by using outsourcing and making visible excess capacity in the organization. The low investment level in the industry is also a concern with respect to the present regulatory model.

As a part of the deliberations initiated by the Norwegian regulator NVE[3] in 2003, on the development of a possibly new regulation model from 2007, an introductory study was performed on a cost model

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[3] The Norwegian Water Resources and Energy Directorate.

inspired by activity based costing (ABC)-concepts, and its potential use in the regulation of electricity distribution (Bjørndal, Bjørnenak and Johnsen (2003)). The basic assertion is that a viable regulatory model should take into account that decisions regarding the operations and investments in the electricity networks are performed by independent, business oriented enterprises, and that in order to achieve a dynamic and efficient industry in the long run, it requires an implementation of the regulation model that encourages best practice. This affects how costs are measured, and how investments are dealt with.

The starting point is a suggestion for a more norm based regulation, where a cost model separating customer-related costs, i.e. measuring, invoicing, customer service, etc., and network-related costs i.e. operation, maintenance, losses, etc., applies. There are clear indications that such a separation of the cost base is valid and possible, and that it could and perhaps should be used in the regulation of the companies in the best possible way. For customer-related costs it is suggested to establish a cost norm per customer, based on individual accounts from a selection of companies, alternatively from more aggregated data. For network-related costs it is suggested that the compensation for the cost of capital (depreciation and interest), operation and maintenance etc. is determined based on some ideal new values of the grid and other network related expenses for a given distribution area (real annuity).

However, in this paper we will focus on the performance-based part of the regulation that at present consists of determining individual efficiency requirements from DEA-analyses. In section 2, the present DEA model for distribution companies is described, and we use data from 1996 to 1999 to illustrate, as we see it, several shortcomings of the model. This concern among other things, effects of company size, the use of different versions of the model when it comes to capital costs, and the fact that changes in resource usage are not valued the same way, but may depend on classification. In this setting, we study the effects of assuming separable costs, and what happens with two separate analyses, or if everything is combined into a single model/measurement. Mathematical results are provided for special cases in section 4, along with results from simulation experiments in section 5. Some conclusions are provided in section 6.

2. DEA in the Norwegian regulation regime

The DEA model used by the Norwegian regulator NVE is an input-based cost efficiency model, with variable returns to scale (VRS) (see for instance Cooper et al. (2000)). There are different models for distribution (mainly up to 22 kV) and regional transmission (mainly 22 kV – 132 kV). Different companies are often present at both levels, and must allocate costs between the different network levels in order to provide the input data for the efficiency analyses. In this paper we will focus on the model used for the roughly 160 distribution companies in the Norwegian system.

The observed data for company $j = 1,2,...,n$ are given by the input-vector $\left(x_{1j}, x_{2j}, \ldots, x_{mj}\right)$ and the output-vector $\left(y_{1j}, y_{2j}, \ldots, y_{sj}\right)$. The factor prices of company j are given by the price-vector $\left(w_{1j}, w_{2j}, \ldots, w_{mj}\right)$. The cost-efficiency of company j^* is found by solving the linear programming (LP) problem:

$$\underset{\lambda,z}{\text{Minimize}} \quad \frac{\sum_i w_{ik*} z_i}{\sum_i w_{ik*} x_{ik*}} \tag{1}$$

subject to

$$z_i \geq \sum_k \lambda_k x_{ik} \qquad i = 1,...,m \tag{2}$$

$$y_{jk*} \leq \sum_k \lambda_k y_{jk} \qquad j = 1,...,n \tag{3}$$

$$\lambda_k \geq 0 \qquad k = 1,...,p \tag{4}$$

$$\sum_k \lambda_k = 1 \tag{5}$$

In the LP-problem (1)-(5) the objective is to find the optimal input-vector for company j^*, given by $(\lambda_1,...,\lambda_m)$ and $(z_1,...,z_m)$, and where (2)-(5) guarantees that we are within the production possibility set. Another way to phrase this is that we try to find the least cost of producing j^*s output given j^*s input-prices and the possibility set given by the industries input- and output-combinations. Implicitly, it is assumed that company j^* has access to the same technology as the other companies, but not to the same factor markets. Notice also that (4) and (5) follows from the assumption that we consider convex combinations of the observed data points, and that assuming constant returns to scale (CRS), implies that (5) is removed.

The reported cost-efficiency for company j^* is equal to the ratio (in %) between the cost of the optimal factor combination and the actual cost, i.e. the value of the objective function of the LP problem. If a company has both distribution network and regional transmission, the efficiency measure is a weighted average of the two efficiency numbers, and the weights are set equal to the relative cost shares. In the regulation of the Norwegian grid companies from 2002, the results of the DEA-analyses are used to determine individual efficiency-requirements, and companies are expected to catch up with about 47% of the inefficiency over the 5-year regulation period from 2002 until 2006. This means that a company with an efficiency of 80% gets a yearly individual efficiency requirement of approximately 1.95%. In addition, a general efficiency requirement of 1.5% applies to all the companies in the industry, such that the yearly reduction in allowed revenues for the 80% company would be approximately equal to 3.45%.

The inputs and corresponding factor prices of the DEA model for the distribution companies are the following:

- *Labor* = average number of man-years in the period 1996-1999. The factor price is wages per man-year (1000 NOK).
- *Goods and services* = all costs (average for 1996-1999) except wages, losses capital expenses, and actual value of lost load (VOLL, in the Norwegian system, termed KILE). Goods and services are measured in NOK, i.e. the factor price is equal to 1.
- *Losses* = average yearly energy losses (MWh) for 1996-1999. Losses are valued according to average system of energy for the years 1996-1999, i.e. 0.174 per MWh (1000 NOK).
- *Capital* per 31.12.1999. Two different analyses are carried out, one is based on accounting values, the other on catalogue values of existing capital assets. The factor price for the first

variant is depreciation rate (from the books) + interest rate (NVE reference rate = 8.025%). For the catalogue-value variant, the factor price is an annuity factor, using the reference rate of NVE and average lifetime of assets.

- *Actual VOLL* = lost load for 1996-1999 times standard prices for different customer groups. Since this is measured in NOK, the factor price is equal to 1.

An interesting observation is that the model could be simplified, specifying only three inputs. If factors have the same factor prices across all companies, there will be no effect on the efficiency measures by aggregating the inputs. In the DEA model for distribution companies, goods and services, losses and actual VOLL could be aggregated into a single input measured in NOK.

The outputs of the model are

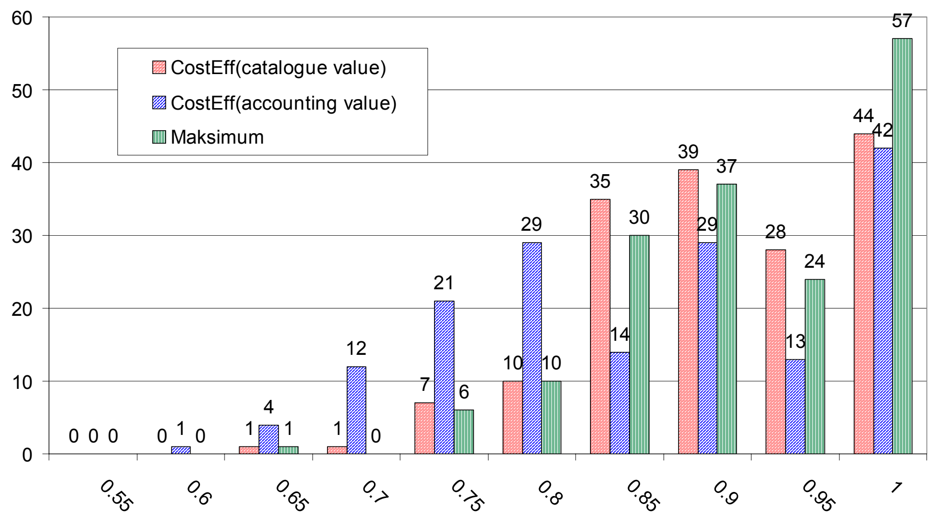
- Low voltage lines (no. of kilometers)
- High voltage lines (no. of kilometers)
- Number of customers
- Delivered energy (MWh)
- Expected VOLL (1000 NOK)

Even though models like the DEA model does not specify a relationship between inputs and outputs, they still imply a number of assumptions and characteristics. In the following we will show a few, some are general while others are due to the specific variant we are considering here.

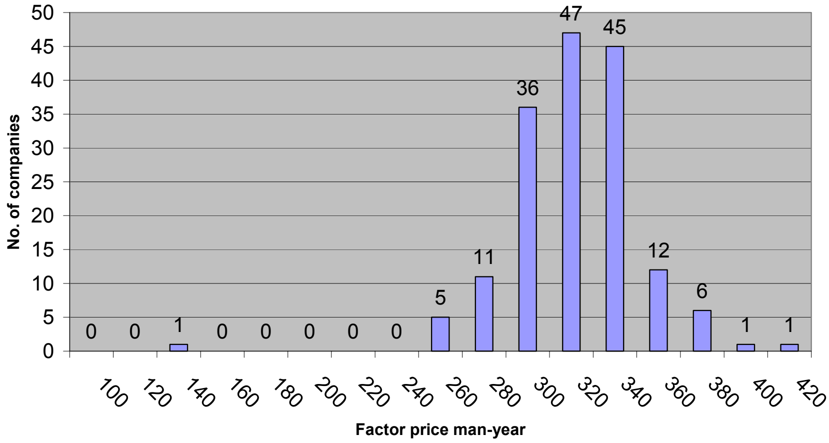
A well-known characteristic of the VRS-variant of the DEA model is that a company which is the largest one with respect to a single output will be 100% efficient no matter what the costs are. This follows from (3). For the distribution companies in Norway, these “automatically” efficient companies comprise a large share of the customer base, having approximately 24% of the total number of customers (ref. table below). Another interesting observation is that Skagerak Nett AS, that is the result of a merger between several companies within the same area, has an efficiency in distribution of about 87%. However, if the DEA-analysis for Skagerak had been run on "merged" data (all other things being equal), Skagerak would be the largest company on low voltage lines, and therefore 100% efficient.

Output	Units	Company	No. of customers
Low voltage lines	8 951	BKK Distribusjon AS	147 500
High voltage lines	4 969	Nord-Trøndelag elektrisitetsnett	73 557
Customers	303 312	Viken Energinett AS	303 312
Delivered energy	8 370 400	Viken Energinett AS	303 312
Expected VOLL	48 089	Troms Kraft Nett AS	59 376

Since NVE runs two variants of the model (ref. capital expenses) and the companies are allowed to choose the best outcome, quite a large portion of the companies turns out to be 100% efficient. The effect of the possibility of choosing the highest efficiency number is illustrated in the figure below.



From the input data of the analyses it is observed that the factor prices of labor vary a lot (ref. figure below). The factor prices are found by dividing total labor cost with the number of man-years reported.

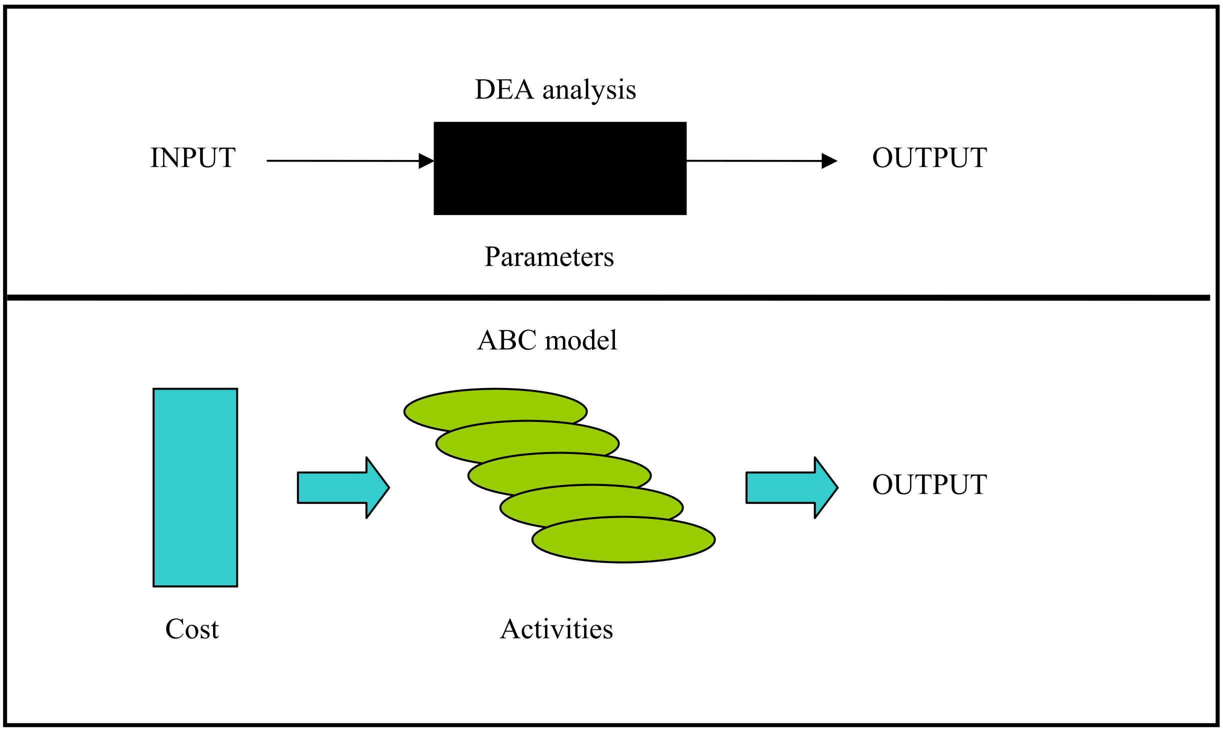


It is quite obvious that the accuracy of this data is low, and particularly, for various reasons identified, there is considerable uncertainty about the number of man-years. This may influence the efficiency numbers in unpredictable ways as changes in factor usage has a stronger effect on efficiency than changes in factor price, even though the changes have the same effect on total cost! This is illustrated by the example in the table below. The starting point is a company with 94.05 reported man-years, wages per man-year of 311 112 NOK, and a total labor cost of 29 260 084 NOK. The efficiency of the company is 87.96%. In the table below we illustrate the effect of reducing the cost to 23 512 500 NOK, and we see that the "best" way of doing this is to reduce the number of man-years (row 2). This has a considerably larger effect on the efficiency as compared to reducing the cost per man-year (row 1).

Man-years	Wage per man-year	Total cost	Cost efficiency	Change
94.05	250 000	23 512 500	88.59%	0.63%
75.58	311 112		91.02%	3.06%

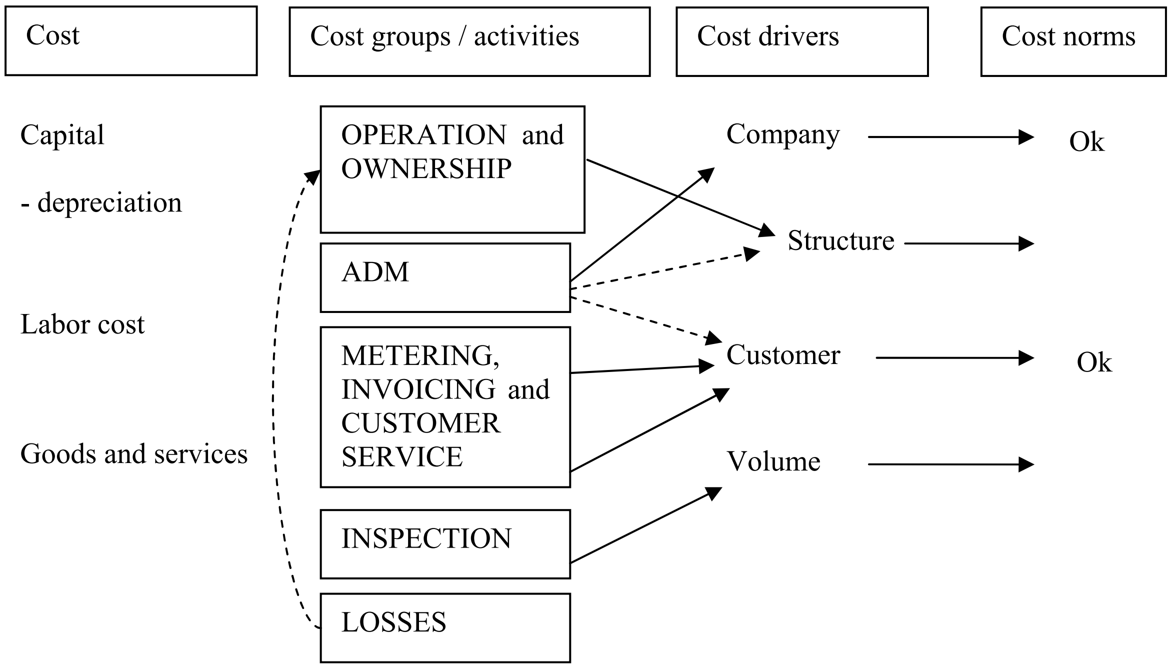
3. Activities and costs in the distribution companies

In Bjørndal et al. (2003) we were concerned about the information value of the regulatory model, not only for the regulator, but also for the regulated firm. An advantage with the DEA-model is that it does not assume a specific relationship between inputs and outputs, for instance through a specific functional form of the production function. On the other hand, this also makes it difficult to understand and explain the reasons for the (in)efficiency of a specific firm. The activities are treated like a "black box", which makes it difficult to focus improvement efforts, and it also undermines the legitimacy of the efficiency model (see figure below).



Structural models, like for instance the ABC model on the other hand, attempts at opening up the activities of the companies, seeking to evaluate the efficiency of specific tasks. The disadvantages are of course that they are based on strong assumptions about separability, linearity and homogeneity of the cost groups. These assumptions are especially problematic for the network-related costs (operation, ownership and losses, see figure below), where structural factors like topology, climate, population density etc. are assumed to be major cost drivers, and there is no "easy" relationship between the factors and the costs. This means that the ABC methodology is not a natural candidate for the total cost base.

However, a natural distinction can be drawn between network-related costs, and the costs of servicing customers. This includes metering, invoicing, customer service, inspection and also to a certain extent administrative activities. For this part of the cost base, which amounts to roughly 20% of the total costs, it should be possible to determine a cost norm per customer.



In the next sections we will consider some effects of failing to utilize the mild form of cost structure that is constituted by costs being separable.

4. Consequences of model misspecification

The present regulation scheme evaluates the cost efficiency of the distribution companies using a single DEA model, where input and output factors for both network and customer activities are included. Alternatively, one could have used separate models for each activity, and computed the overall efficiency for each company (or decision making unit, DMU) as a weighed average. Our hypothesis is that the use of a single model introduces a bias in the efficiency estimates, and this has two reasons:

(A) The reference set, given by the value of the λ's, has to be the same for both activities when a single model is used. This is, as we will show below, equivalent to adding extra constraints in the LP-model used to compute the efficiencies, and thus leads to a positive bias in the efficiency estimates.

(B) Since the two activities have similar input factors, these are aggregated in the single model. The effect on the efficiency estimates arising from this aggregation is unclear.

In order to show the effect of (A) formally, suppose that each DMU $k = 1,...,p$ is engaged in two activities 1 and 2, where activity 1 uses n^1 inputs to produce m^1 outputs, while activity 2 uses n^2 inputs to produce m^2 outputs. Let the amounts of input used by DMU k in activity $\lambda \in \{1,2\}$ be given by x_{ik}^{λ}, where $i = 1,...,m^{\ell}$, and the amounts of output produced be given by y_{jk}^{λ}, where $j = 1,...,n^{\ell}$. The efficiency of DMU $k*$ with respect to activity ℓ can be found by solving the following LP-problem, similar to (1)-(5):

$$\underset{\lambda^{\lambda},z^{\lambda}}{\text{Minimize}} \quad \frac{\sum_i w_{ik*}^{\lambda} z_i^{\lambda}}{\sum_i w_{ik*}^{\lambda} x_{ik*}^{\lambda}} \tag{6}$$

subject to

$$z_i^{\lambda} \geq \sum_k \lambda_k^{\lambda} x_{ik}^{\lambda} \qquad i = 1,...,m^{\ell} \tag{7}$$

$$y_{jk*}^{\lambda} \leq \sum_k \lambda_k^{\lambda} y_{jk}^{\lambda} \qquad j = 1,...,n^{\ell} \tag{8}$$

$$\lambda_k^{\lambda} \geq 0 \qquad k = 1,...,p \tag{9}$$

$$\sum_k \lambda_k^{\lambda} = 1 \tag{10}$$

Let E^1 and E^2 denote the optimal value of (6)-(10) for activities $\ell = 1$ and $\ell = 2$, respectively, and let $(\hat{\lambda}^{\lambda}, \hat{z}^{\lambda})$ denote the optimal values of the decision variables. The cost efficiency of DMU k^* with respect to activity ℓ is given by $E^{\lambda} = \hat{C}^{\lambda} / C^{\lambda}$, where $\hat{C}^{\lambda} = \sum_{i=1}^{m_{\lambda}} w_{ik*}^{\lambda} \hat{z}_i^{\lambda}$ and $C^{\lambda} = \sum_{i=1}^{m_{\lambda}} w_{ik*}^{\lambda} x_{ik*}^{\lambda}$. The overall efficiency of the DMU is given by

$$E = \frac{\hat{C}^1 + \hat{C}^2}{C^1 + C^2} = \frac{\hat{C}^1}{C^1} \frac{C^1}{C^1 + C^2} + \frac{\hat{C}^2}{C^2} \frac{C^2}{C^1 + C^2} = E^1 \frac{C^1}{C^1 + C^2} + E^2 \frac{C^2}{C^1 + C^2}. \tag{11}$$

In order to study the effect of aggregating activities, note that E can also be computed by solving the following problem:

$$\underset{\lambda,z}{\text{Minimize}} \quad \frac{\sum_{i=1}^{m_1} w_{ik*}^1 z_i^1 + \sum_{i=1}^{m_2} w_{ik*}^2 z_i^2}{\sum_{i=1}^{m_1} w_{ik*}^1 x_{ik*}^1 + \sum_{i=1}^{m_2} w_{ik*}^2 x_{ik*}^2} \tag{12}$$

subject to

$$z_i^\lambda \geq \sum_k \lambda_k^\lambda x_{ik}^\lambda \qquad i = 1,\ldots,m^\ell \qquad \ell = 1,2 \tag{13}$$

$$y_{jk*}^\lambda \leq \sum_k \lambda_k^\lambda y_{jk}^\lambda \qquad j = 1,\ldots,n^\ell \qquad \ell = 1,2 \tag{14}$$

$$\lambda_k^\lambda \geq 0 \qquad k = 1,\ldots,p \qquad \ell = 1,2 \tag{15}$$

$$\sum_k \lambda_k^\lambda = 1 \qquad \ell = 1,2 \tag{16}$$

The effect of (A) is equivalent to adding the constraints

$$\lambda_k^1 = \lambda_k^2 \qquad k = 1,\ldots,p \tag{17}$$

to (12)-(16). Adding a constraint will lead to higher (or unchanged) objective function value, and (A) will therefore bias the efficiency estimates upwards.

In order to study the effect of (B), suppose we are using a single model given by (12)-(17), or, equivalently, (1)-(5) with $m = m^1 + m^2$ inputs and $n = n^1 + n^2$ outputs. In order to see what the effect of input aggregation is, consider inputs 1 and 2. Aggregation will affect the following elements of (1)-(5):

$$\underset{\lambda,z}{\text{Minimize}} \quad \frac{w_{1k*} z_1 + w_{2k*} z_2 + \sum_{i=3}^{m} w_{ik*} z_i}{w_{1k*} x_{1k*} + w_{2k*} x_{2k*} + \sum_{i=3}^{m} w_{ik*} x_{ik*}} \tag{18}$$

$$z_1 \geq \sum_k \lambda_k x_{1k} \tag{19}$$

$$z_2 \geq \sum_k \lambda_k x_{2k} \tag{20}$$

In the aggregated problem, (18)-(20) are replaced by

$$\underset{\lambda,z}{\text{Minimize}} \quad \frac{w_{12k*}\left(z_1 + z_2\right) + \sum_{i=3}^{m} w_{ik*} z_i}{w_{12k*}\left(x_{1k*} + x_{2k*}\right) + \sum_{i=3}^{m} w_{ik*} x_{ik*}} \tag{21}$$

$$z_1 + z_2 \geq \sum_k \lambda_k x_{1k} + \sum_k \lambda_k x_{2k} \tag{22}$$

where w_{12k*}. is the factor price of the combined input. Let (λ', z') denote an optimal solution of the aggregated version of (1)-(5). Note that we can always find $\tilde{z}$ such that $\tilde{z}_1 + \tilde{z}_2 = z_1' + z_2'$, $\tilde{z}_i = z_i'$ for $i = 3,...,m$, and such that $(\lambda', \tilde{z})$ is feasible in the original version of (1)-(5). Also, note that the value of (21) is the same for $(\lambda', \tilde{z})$ as for (λ', z'). Hence, the replacement of (19) and (20) by (22) has no effect on the computed efficiency. Hence, the effect of (B), if there is any, must come from the change in the objective function, i.e., replacing (18) by (21). It is unclear what the direction of the bias is, although there are some special cases where we can show that the bias equals zero, which is the case if

$$w_{12k*} = w_{1k*} = w_{2k*}, \tag{23}$$

i.e., if the aggregated input factors have identical factor prices. Another case where aggregation has no effect is where the new factor price is a weighted average of the individual factor prices, and where the weights correspond to “optimal” input usage, i.e., if

$$w_{12k*} = w_{1k*} \frac{x_{1k*}}{x_{1k*} + x_{2k*}} + w_{2k*} \frac{x_{2k*}}{x_{1k*} + x_{2k*}}, \tag{24}$$

$$\text{where } x_{1k*} = \bar{z}_1 \text{ , } x_{2k*} = \bar{z}_2 \text{ , and } \bar{z} \text{ is optimal in (1)-(5).} \tag{25}$$

With respect to the Norwegian distribution companies, the aggregation of “services and goods” is performed according to (23). The aggregation of “man-years” satisfies (24), and, in the cases where DMU k^* is efficient, (25).

5. A simulation experiment

In order to compute DEA estimates for customer and network activities separately, one would need more detailed cost data from each company than is currently being reported to the regulator. With respect to the input factors that are currently included in the model, there are three factors, namely capital, man-years, and services and goods, that need to be allocated among the two activities. From discussions with people in the industry, as well as the fact that customer activities are in fact outsourced by some of the companies, we have the impression that such a separation of costs is indeed feasible. However, for the purposes of this paper we do not have this information available. In order to investigate the misspecification bias, we have instead performed a simulation experiment. Our experiment is similar to the work of Smith (1997), who investigates the effect of omitting input variables, including extraneous input variables, or using a DEA model that is misspecified with respect to returns to scale. A similar analysis is that of Galagadera and Silvapulle (2003), who use a different experimental setup.

The experiment has 160 DMUs, and each DMU has two activities 1 and 2, where $n^1 = 3$, $n^2 = 1$, and $m^1 = m^2 = 2$. In order to simplify the notation, we drop the subscripts referring to the DMU, and label the four outputs y_1, y_2, y_3, and y_4, where output 1-3 belong to activity 1, and output 4 belong to activity 2. Likewise, for the inputs, we label them x_1, x_2, x_3, and x_4, where input 1 and 2 (3 and 4) belong to activity 1 (2). Our technology is similar to the example used in Cornell (1992)[4], and the technology of activity 1 is given by

$$y_1^2 + y_2^2 + y_3^2 = (x_1 x_2)^\alpha, \tag{26}$$

whereas for activity 2 we have

$$y_4^2 = x_3 x_4 . \tag{27}$$

Thus, activity 1 has increasing (decreasing) returns to scale iff $\alpha >$ (<) 1, and constant returns to scale iff $\alpha = 1$. Activity 2 has constant returns to scale. The form of the technology chosen here is a Cobb-Douglas type production function, as is also the case in Smith (1997) and Galagadera and Silvapulle (2003). Smith (1997) uses a technology with one output factor and 2-6 input factors, whereas the technology used by Galagadera and Silvapulle (2003) has three output factors and 1-6 input factors[5].

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[4] Section 5.9

[5] Galagadera and Silvapulle (2003) use a technology that is different from ours with respect to the interaction between outputs, and where input usage is separable. Instead of (26), a model similar to theirs would imply a $y_{ij} = (x_{1j} x_{2j})^{1/2\alpha}$ for each output j = *1,2,3*, and where total input usage is the sum over all outputs, i.e., $x_1 = \sum_{j=1}^{3} x_{1j}$ and $x_2 = \sum_{j=1}^{3} x_{2j}$.

As in the Norwegian distribution companies, one of the output factors of the two activities are identical, i.e.,

$$y_4 = y_3 . \tag{28}$$

Based on this technology, we generated 24 samples, each with 160 DMUs. The samples differ with respect to returns to scale in activity 1 (α = 0.8 / 1.0 / 1.2), as well as the magnitude and type of inefficiency introduced in the data. For each DMU, we first generated data corresponding to a cost efficient solution, and then introduced inefficiency for the respective activities by drawing random numbers γ_1 and γ_2. The efficiencies of the two activities will then be 1 - γ_1 and 1 - γ_2, respectively. "Low" means that the activity is relatively inefficient, i.e., that inefficiency is drawn from the interval [0%,70%], while "High" means that the activity is relatively efficient, in which case the inefficiency is drawn from the interval [0%,10%]. More details about how the samples where generated can be found in the appendix.

The average true efficiency for each sample is shown in Table 1. DEA efficiencies were first computed using separate models for the two. The weighted efficiency estimate, given by (11), was then compared to the estimate from the misspecified model, i.e., a model where the reference sets of both activities were forced to coincide, and the input factors of the activities were aggregated. When combining factor prices, we used (24).

α	Efficiency		Type of inefficiency	
	Activity 1	Activity 2	Allocative	Technical
0.8	Low	Low	62.39	61.65
	Low	High	67.53	67.76
	High	Low	87.13	88.79
	High	High	94.41	94.58
1.0	Low	Low	62.83	60.86
	Low	High	71.60	73.97
	High	Low	78.62	80.08
	High	High	95.22	94.45
1.2	Low	Low	62.00	63.41
	Low	High	78.61	76.41
	High	Low	76.27	73.00
	High	High	95.09	94.81

Table 1 Average (true) efficiencies for the data sets

It is well known that use of DEA in itself leads to overestimation of efficiencies, and this is confirmed by the results in Table 2, where the results from weighted DEA model is compared to the true efficiencies in (1). The results in (2), where bias caused by using the misspecified model instead of weighted DEA, shows that on average, misspecification lead to an overestimation of the efficiencies in all the cases. The bias is relatively large for those samples where activity 2 is relatively inefficient, i.e., the Low-Low and High-Low cases, whereas the bias seems to be smallest when both activities are efficient. The assumptions with regard to returns to scale and the type of efficiency does not seem to influence the bias much.

α	Efficiency		Type of inefficiency			
	Activity 1	Activity 2	Allocative		Technical	
			(1)	(2)	(1)	(2)
0.8	Low	Low	7.31	**4.60**	8.62	**6.06**
	Low	High	8.57	**0.61**	9.55	**0.46**
	High	Low	1.81	**2.88**	2.51	**2.62**
	High	High	1.79	**0.62**	2.48	**0.62**
1.0	Low	Low	4.79	**5.53**	7.28	**5.79**
	Low	High	4.85	**1.18**	6.21	**1.60**
	High	Low	0.97	**4.70**	2.34	**4.22**
	High	High	1.05	**0.65**	2.57	**1.23**
1.2	Low	Low	3.54	**6.75**	4.94	**6.88**
	Low	High	2.85	**2.25**	4.76	**2.08**
	High	Low	1.17	**4.39**	1.84	**4.80**
	High	High	0.78	**0.74**	1.71	**1.26**

Table 2 Average bias from (1) using weighted DEA compared to true efficiencies and (2) from using the misspecified DEA model

In Table 3 we show the correlation between rankings based on the two DEA approaches versus the rankings based on the true efficiencies. As expected, the correlation coefficients are, for most of the samples, higher when we use weighted DEA than when we use the misspecified model. Whereas we found the Low-Low and High-Low samples to have higher biases than the remaining samples, the picture is not so clear when we look at rank correlation.

α	Efficiency		Type of inefficiency					
	Activity 1	Activity 2	Allocative			Technical		
			(1)	(2)	Diff.	(1)	(2)	Diff.
0.8	Low	Low	0.81	0.78	0.03	0.83	0.86	-0.02
	Low	High	0.77	0.78	-0.01	0.71	0.74	-0.03
	High	Low	0.93	0.65	0.28	0.93	0.84	0.10
	High	High	0.73	0.61	0.12	0.75	0.75	-0.01
1.0	Low	Low	0.91	0.82	0.08	0.88	0.80	0.07
	Low	High	0.82	0.82	0.00	0.83	0.84	-0.01
	High	Low	0.99	0.78	0.22	0.96	0.83	0.13
	High	High	0.78	0.55	0.23	0.63	0.54	0.09
1.2	Low	Low	0.91	0.78	0.13	0.93	0.80	0.13
	Low	High	0.91	0.86	0.06	0.89	0.87	0.02
	High	Low	0.99	0.88	0.11	0.99	0.85	0.14
	High	High	0.90	0.52	0.37	0.86	0.74	0.12

Table 3 Spearman rank correlation coefficients between (1) ranks based on weighted DEA versus true efficiencies, and (2) ranks based on misspecified model versus true efficiencies.

Even though the average bias caused by misspecification may not be large in many cases, it can be large for some DMUs. This is illustrated by Table 4, where we see that a considerable proportion of the DMUs have biases in excess of 10% in many of the samples, especially in Low-Low and High-Low samples. Hence, the effect of using the misspecified model can be dramatic for some DMUs, which is especially relevant in the Norwegian setting, where the efficiency estimates are actually used to determine the allowable income of the distribution companies. We also see many DMUs where the bias is negative, which is due to the aggregation of input factors, described as effect B in Secion 4. An interesting observation based on the numbers in Table 4 is that the shape of the distributions seems to depend on the type of inefficiency present in the data. The samples with allocative inefficiency have a flatter distribution than the samples with technical inefficiency, which can also be seen from the standard deviations presented in Table 5.

α	Efficiency		Type of inefficiency							
	Activity 1	Activity 2	Allocative				Technical			
			< -5%	< 0%	≥ 10%	≥ 20%	< -5%	< 0%	≥ 10%	≥ 20%
0.8	Low	Low	1	13	14	1	0	0	12	0
	Low	High	1	27	1	0	0	18	0	0
	High	Low	3	17	7	1	0	4	2	0
	High	High	1	18	0	0	0	4	0	0
1.0	Low	Low	2	14	19	4	0	5	21	1
	Low	High	6	31	1	0	0	14	0	0
	High	Low	4	17	9	4	0	8	8	3
	High	High	2	26	0	0	0	8	0	0
1.2	Low	Low	2	9	22	4	0	1	16	6
	Low	High	4	22	4	1	0	14	0	0
	High	Low	1	19	11	2	0	8	8	6
	High	High	4	24	0	0	0	6	0	0

Table 4 Distribution of the misspecification bias. Numbers indicate the percentage of DMUs with bias below/above the given treshold values

α	Efficiency		Type of inefficiency			
	Activity 1	Activity 2	Allocative		Technical	
			(1)	(2)	(1)	(2)
0.8	Low	Low	11.40	**5.12**	10.04	**3.33**
	Low	High	11.60	**2.04**	13.26	**0.67**
	High	Low	2.38	**4.66**	1.87	**2.70**
	High	High	1.76	**1.30**	1.74	**0.51**
1.0	Low	Low	7.62	**6.99**	8.02	**5.24**
	Low	High	9.33	**3.41**	7.93	**1.65**
	High	Low	1.11	**7.75**	3.04	**4.84**
	High	High	1.34	**1.97**	1.69	**1.03**
1.2	Low	Low	7.27	**7.26**	6.30	**7.16**
	Low	High	4.92	**4.01**	5.91	**2.17**
	High	Low	2.07	**5.98**	1.43	**8.27**
	High	High	0.97	**2.34**	1.13	**1.20**

Table 5 Standard deviation of the bias from (1) using weighted DEA compared to true efficiencies and (2) from using the misspecified DEA model

In Section 4 we showed that the misspecification has two sides, i.e., forcing the same reference sets for both activities and aggregating input factors. In Table 6 we have decomposed the misspecification bias according to these two effects. This was done by using (12)-(16) in order to compute the "correct" efficiency of each DMU. The effect of forcing the same reference set is computed by imposing (17) in addition to (12)-(16), and this corresponds to (A) in Table 6, where (B) is the additional effect of aggregating inputs. The results show that the dominating effect is that of forcing the same reference set, while aggregating inputs has a negative impact on the estimated efficiency.

α	Efficiency		Type of inefficiency			
	Activity 1	Activity 2	Allocative		Technical	
			(A)	(B)	(A)	(B)
0.8	Low	Low	4.69	-0.09	6.38	-0.32
	Low	High	0.75	-0.14	0.65	-0.19
	High	Low	3.33	-0.45	3.06	-0.45
	High	High	0.79	-0.16	0.78	-0.17
1.0	Low	Low	6.01	-0.48	6.37	-0.58
	Low	High	1.57	-0.39	2.02	-0.43
	High	Low	5.01	-0.31	4.95	-0.73
	High	High	1.11	-0.46	1.60	-0.37
1.2	Low	Low	6.97	-0.22	7.52	-0.64
	Low	High	2.03	0.23	2.55	-0.48
	High	Low	4.49	-0.10	5.26	-0.46
	High	High	1.28	-0.54	1.69	-0.44

Table 6 Decomposition of average misspecification bias

6. Conclusion and future research

In this paper we have investigated the DEA model as used in the regulation of the Norwegian distribution companies, and with a simulation experiment we have illustrated the importance of using information on the structure of the cost functions, even if this information is very "mild", i.e. we don't know the exact form, but only know that some costs are separable, and that it is possible to distinguish the resources used in one activity from resources used in other activities. We have argued that there is reason to believe that it is possible to distinguish between customer-related costs and network-related costs in the distribution companies, and that this distinction should be used in the performance measurements.

In the present regulation of the grid companies, cost allocations between different activities are performed already. One distinction is between the costs of running and developing the network and costs related to other business areas, like electricity production, telecommunication, alarm services etc. Another distinction is related to the network levels. As described in section 2 there are different DEA models for distribution and regional transmission companies. However, many companies have network activities belonging to both grid levels, and therefore have to perform an allocation of costs to the different network levels. An erroneous cost allocation may impact the results, both for the company being measured, but it may also influence on the efficient frontier of the DEA model, and thereby indirectly affect the results on the other companies in the sample. There are many indications that the allocation of cost between the grid levels is at best arbitrary. Distinguishing between customer-related and network-related costs may constitute a better way.

Finally, the advantage of using all readily available information on cost structures in the efficiency measurements is not restricted to regulators obtaining improved information of the efficiency of the companies. The information to the regulated firms are also improved, in that a model, measuring the efficiencies of the separate activities, gives indications to the regulated firms where it is possible to improve on its operations.

Appendix

For a given DMU, output factor values and factor prices for inputs were drawn from uniform distributions on the intervals [50,100] and [5,10], respectively, and values for the input factors were then generated in order to construct a cost efficient DMU. In general, given an output vector ***y***, a vector of input factor prices ***w***, and a functional relationship **y** = *f(***x***)* describing the technology, a cost efficient input vector is a solution of the program $\min_{x}\{wx : y = f(x)\}$. The optimal input factor values are given by

$$x_1 = \left(y_1^2 + y_2^2 + y_3^2\right)^{1/2\alpha} \sqrt{\frac{w_2}{w_1}} \text{ and } x_2 = x_1 \frac{w_1}{w_2}, \tag{29}$$

and for activity 2,

$$x_3 = y_4 \sqrt{\frac{w_4}{w_3}} \text{ and } x_4 = x_3 \frac{w_3}{w_4}. \tag{30}$$

Technical inefficiency was introduced by simply scaling up the values for the input factors, given the randomly generated inefficiency numbers γ_1 and γ_2, i.e., by computing the "actual" values

$$\tilde{x}_1 = \frac{x_1}{1-\gamma_1},\ \tilde{x}_2 = \frac{x_2}{1-\gamma_1},\ \tilde{x}_3 = \frac{x_3}{1-\gamma_2}, \text{ and } \tilde{x}_4 = \frac{x_4}{1-\gamma_2}, \tag{31}$$

for the input factors.

In the case of allocative inefficiency, the actual values for the input factors of activity 1 are generated by solving the equation system given by

$$1-\gamma_1 = \frac{w_1 x_1 + w_2 x_2}{w_1 \tilde{x}_1 + w_2 \tilde{x}_2}, \tag{32}$$

i.e., the efficiency of the DMU is set equal to γ_1, while at the same time making sure that the DMU is technically efficient, i.e. that (26) is satisfied. The solution to (26) and (32) is given by

$$\tilde{x}_1 = x_1 \frac{1 \pm \sqrt{2\gamma_1 - \gamma_1^2}}{1-\gamma_1} \text{ and } \tilde{x}_2 = x_2 \Bigg/ \frac{1 \pm \sqrt{2\gamma_1 - \gamma_1^2}}{1-\gamma_1}, \tag{33}$$

where “±” indicates that the desired inefficiency can be obtained in two ways, either by increasing (decreasing) the amount of input 1 (2), or by decreasing (increasing) the amount of input 1 (2). We used the first approach for half of the DMUs in each data set, while the second approach was used for the other half. The introduction of allocative inefficiency for activity 2 was done in a similar manner, and we omit the details here.

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