Model specification

PROJECT GERNER

Per Agrell
Peter Bogetoft

2006-04-07

Disclaimer

This is an interim report on model specification and variable selection in the GERNER project on the development of an efficiency measurement model for electricity and gas distribution, commissioned by Bundesnetzagentur (*BNA*), under the supervision of the authors, professors Per AGRELL and Peter BOGETOFT for SUMICSID AB.

The modeling and calculations behind this report are based on confidential data material submitted to and obtained by the Bundesnetzagentur, but it may contain errors in the original reporting, transmission or interpretation. All individual and/or sector calculations of performance are intended to identify appropriate model structures and not to make individual estimates of firm efficiency. No numeric estimates of efficiency, costs or revenues will be given in this report.

The recommendations in the report have not been subject to review from the

Sumicsid AB
Tunbyn 502
S-85590 SUNDSVALL, SWEDEN
www.sumicsid.com

1. Model specification

Method

STEPS IN A BENCHMARKING STUDY

1.01 The value of benchmarking tools – as most tools – depend on how skillfully they are used. With the forthcoming of professional computer codes, the ease of efficiency analyses has increased – and hereby also the risk of un-reflected misuses of the frontier approaches. A particular problem in the business of frontier modeling is the lack of simple warning indicators and model specification tests. The risk increases when the modelers do not have string methodological training. Text books seldom contains detailed guidelines for proper uses of the tools they describe. A safeguard against misuses is sound application procedures. We now outline a series of relevant steps in such a procedure.

1.02 The model development includes the following steps: 1) Analysis of regulatory interface with benchmarking (preference structure and application), 2) Choice of model structure, orientation and evaluation horizon, 3) Choice of production technology (returns to scale and disposability), 4) Choice of variables and environmental proxies, 5) Choice of estimation approach (parametric or non-parametric)

1.03 The steps are illustrated in figure 4.3 below. We now comment on the individual steps.

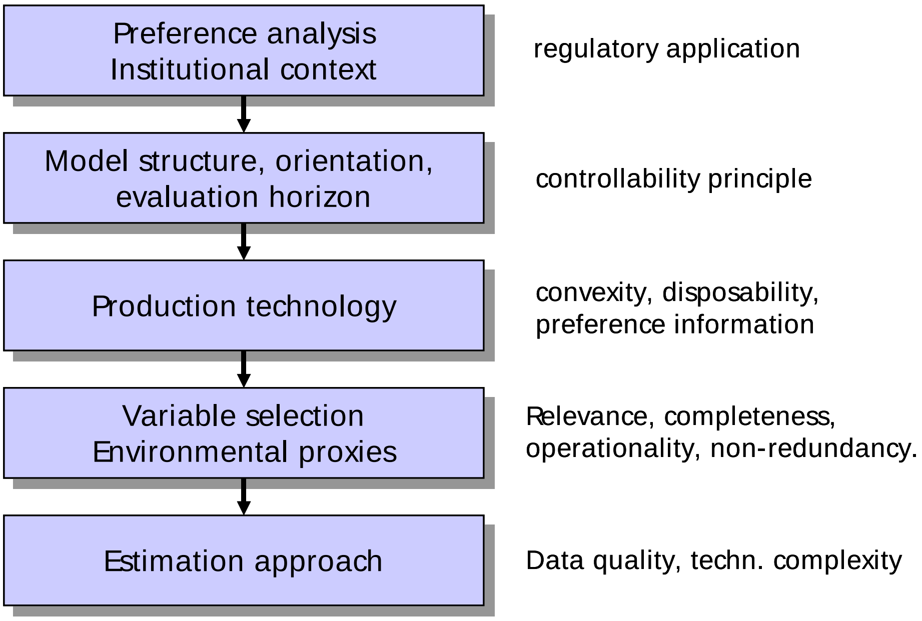

Figure 4.3 Model development steps

Regulatory interaction

1.04 The regulatory approach and the benchmarking model are closely interdependent. This is the general theme of this report. Here we simple remind that the scope, frequency and scale of the regulation regime shall ideally guide the choice of optimal benchmarking method. In repeated moderately incentivized settings with audited data collection, deterministic non-parametric methods, such as data envelopment analysis DEA, are often selected as primary benchmarking tools. In one-shot assessments of incumbent inefficiency and settings with high-powered regimes and potentially noisy data, parametric approaches, such as stochastic frontier analysis SFA or multi-output econometrics, are appropriate.

1.05 It is also important to adapt the benchmarking approach to current legislation, as well as to the long-term vision of the regulator. The methodology for this sort of *dynamic regulatory trajectory* has been subject to study in Agrell and Bogetoft (2001, 2003a) and Estache and Martimort (1998).

Model structure

1.06 The modeling proceeds to investigate the activity under the *controllability principle*. The idea is to tailor the evaluation horizon with the degree of controllability over the activity, if necessary splitting the comprehensive model in a long-run and a short-run model. In distribution regulation, this corresponds to the need to incentivize efficient infrastructure investments as well as efficient grid operation (Sweden, Finland and Norway). However, regulation may also start by assessing stranded cost due to inefficient investments and then operate a comprehensive long-run model with the adjusted capital input (Holland, UK and Denmark).

1.07 The *orientation* is normally given by the controllability principle as well. That it, the discretionary and non-discretionary variables are identified and discretionary inputs (or outputs) are reduced (or expanded). In transmission benchmarking, the focus is usually on cost minimization in a unbundled cost structure, but more advanced solutions may be relevant for integrated utilities. The recent development of directional distance functions offers a flexible approach that can take into account both the *controllability* of different resources and the preferences towards alternative directions.

1.08 The *preferences* for alternative improvement directions may reflect the regulator's trade-offs, say between economic and environmental concerns. Alternatively, the preferences may reflect intra-firm improvement strategies, e.g. as they are settled depending on the relative power of different employee groups.

Production technology

1.09 Non-parametric as well as parametric models usually convexity assumptions, disposability assumptions and return to scale assumptions.

1.10 Most models use a global *convexity* assumption. That is they assume that any weighted average of any pair of feasible productions plans are feasible as well. Although it is widely used and can be motivated in some cases, it is fair to say that it is traditionally assumed for technical convenience to simplify the duality between the production and cost space. Also, in efficiency studies it is done to increase the discriminatory power by extending the production possibility set. On the other hand, there is by now a series of models invoking less convexity assumptions, e.g. Agrell and Tind(2001), Bogetoft(1996), Bogetoft, Tama, Tind(2000), Borger and Kerstens(1996), Deprins, Simar and Tulkens(1984), Petersen (1990), Tulkens(1993). These models are theoretically appealing as they rely less on a priori assumptions and they are in general easier for the industry to accept as they rely less on the idea of mixed organizations – and of course tend to put everyone in a better light.

1.11 In terms of *disposability, i.e.* whether or not the production space is characterized by congestion constraints, rather strong assumptions are usually imposed, say strong free disposability where more inputs can always produce less outputs.

1.12 In terms of *return to scale*, the traditional models either make no assumptions or presume a – possibly local – version of the constant return to scale hypothesis. There are several common motivations to use a constant return to scale assumption like in Norway, i.e. to assume that if we adjust inputs up-ward or down-wards with a given factor, we can do the same on the output side and vice versa. One is that one can always use multiples of smaller units. This prohibits decreasing return to scale were more inputs generates small and smaller increases in the output. A second is – as with convexity – to retain sufficient discriminatory power. A third is that we would like companies to work on the constant return to scale parts of a technology to ensure that they have the right scale.

1.13 The basic assumptions of an efficiency analysis model should ideally be tested. Validation with *statistical tools* allows the analyst to settle on the right model with arguments that withstand industry challenge. There is a growing literature on statistical test but an early approach by Banker(1996) can be used to test all of the above models, i.e. the validity of a constant return to scale assumption, a free disposability assumption and a convexity assumption.

Variables and environmental proxies

1.14 The choice of variables for a given model structure involves looking for a set that is *relevant, complete, operational* and *non-redundant.*

1.15 *Relevance* means that the set of variables should reflect the industry's and the authority's comprehension of the system. The variables should be defined such that decision makers and legislators can relate to and refer to them in the regulation. In the modeling, a compromise is found in the interval between the industry's process-oriented desire to capture the details of the process and the authority's tendency to aggregate to increase comparability.

1.16 *Completeness* means that the set of variables fully capture the objectives (or regulated costs/revenues) of the decision making units. Non-modeled activities are to be explicitly acknowledged to avoid opportunistic action.

1.17 *Operationality* makes it preferable to use variables that are unambiguously defined and measurable. Qualitative indexes, subjective assessments of utility or service value are inadequate in this sense.

1.18 *Non-redundancy* is another word for Occam's razor, prescribing the least complicated means that achieves the end. Overlapping and partially redundant variables may interfere and introduce avoidable noise in the analysis.

1.19 The *model's degree of freedom* is a technical concept that relates the number of observations to the dimensionality of the model. The lower the dimensionality of the model, the higher it's discretionary ability. In the parametric, statistical model, the concept is related to the power of subsequent hypothesis tests. In the non-parametric models, heuristic upper limits on the number of variables have been proposed as well. They require that the number of observations must exceed 3*(no of inputs + no outputs) or (no inputs)(no outputs). With a fair number of distribution companies, this allows for rather flexible non-parametric models.

1.20 Regulatory benchmarking is the art of ensuring a fair treatment of all firms without leaving excessive rents. The proper use of *environmental variables* in the benchmarking models assures these two conflicting objectives. Categorical variables are related to climate, topology, density or other imposed regional heterogeneity in operating conditions. In particular mountainous regions such as Austria, Sweden and Norway are subject to such conditions, whereas models for the fairly homogenous countries in Western Europe have ignored this aspect. E.g., the final regulatory models for Sweden 2000 in Agrell and Bogetoft (2002), included four control variables (climate zone[1], transforming capacity/interconnection station, subscribed capacity in MW, minimal spanning net-length). However, we recommend that the final choice of environmental variables be made after exhaustive pilot-runs with alternative configurations and statistical tests like above. In this manner, the regulator has access to convincing evidence to various objections to the benchmarking by the regulated firms.

1.21 The choice of variables for the model need not be unique. It can in many case we useful to have an *arsenal of complementary models*. First of all, it gives more credibility to the results if they are verified in a series of models. Secondly, to the extent that the different specifications lead to contradicting results, one can let the benefit of the doubt protect the evaluated – like it is done in a Norwegian context with respect to alternative capital measures. The idea of picking the best result fits particularly nicely with the DEA idea of putting everyone in their best possible light. In fact, DEA results can be interpreted as the best results one can obtain using linear (or convex) cost functions, cf. Bogetoft(2000). Thirdly, using a spectrum of specification can be useful to understand the nature of the

[1] The climate zone was suppressed in 2002 after statistical tests to coordinate with the Network Utility Model, which does not control for climate.

inefficiency and to decompose the differences among them. Again this has a nice theoretical basis as several types of inefficiency, e.g. technical, scale and allocative inefficiencies are defined precisely from the effects of using one or another model assumption. The use of models with different variables is probably less common than the use of different model assumptions like return to scale assumptions. Still, it is routinely done in second stage analysis of the results. Also, in a Swedish context we have found it very useful to work with cost models that has either direct operating expenditure or direct consumer charges as inputs, cf. chapter 6. By comparing the outcome of the two, one can identify if more efficient companies simply generates more profit to the owners and one can better identify possible strategic behavior

Estimation approach

1.22 In the principal choice of an estimation method, a number of issues can be used to evaluate the appropriateness of a particular method. We discussed four classes of estimation methods above, and summarized some of their strength and weaknesses. Here we simple remind that one of important concerns from the point of view of designing incentives based on benchmarking models is the (partial) choice between flexibility and robustness to noise.

STEPS IN MODEL IMPLEMENTATION

1.23 In applied research, it is of course not enough to have good theoretical models and good scientific procedures for how to chose models etc. It is also important to have a good implementation of whatever model is decided on. We discuss a few issues that we find particularly important in the implementation of benchmarking models in a regulatory context.

1.24 The model implementation phase includes steps like 1) Choice of software platform, 2) Implementation of the chosen model using the software, 3) Data validation and review, 4) Experimental design for pilot-runs, 5) Execution of runs, 6) Output analysis. The steps are illustrated in figure 4.4 and commented on below.

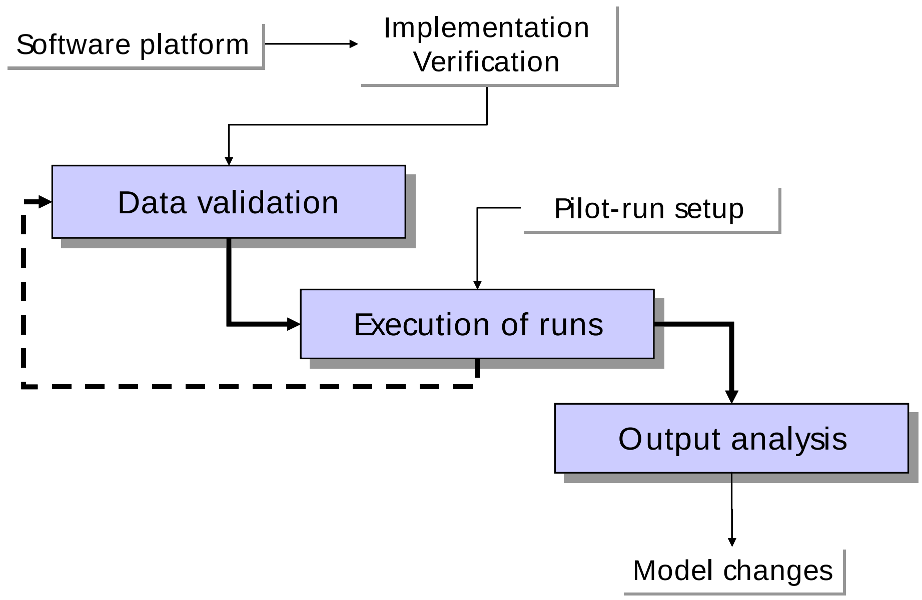

Figure 4.4 Stages in model implementation

Software platform

1.25 For the calculations in this round have been used the statistical platform R and the SFA code Frontier 4.1. The open platform has the advantage of constructing time saving customized solutions (scripts) to perform even complex estimation tasks, including the outlier detection.

Implementation and verification

1.26 In order to minimize implementation errors, it can be useful to cross-validated preliminary models with other software. For many of the dedicated software various types of numerical problems have been demonstrated.

Data validation

1.27 *Outlier analysis* consists of screening extreme observations in the model against average performance. Depending on the approach chosen (DEA, SFA), outliers may have different impact. In DEA, particular emphasis is put on the quality of observations that define best practice. The outlier analysis in DEA can use statistical methods as well as the dual formulation, where marginal substitution ratios can reveal whether an observation is likely to contain errors. In particular, observations that have a disproportionate impact (influence or leverage) on the sign, size and significance of estimated coefficients are reviewed using a battery of methods that is described below.

1.28 Specfic functions in R provide direct access to the corresponding diagnostic quantities for the regression coefficients and the residual error. (These re-normalize the residuals to have unit variance, using an overall and leave-one-out measure of the error variance respectively.) Values for generalized linear models are approximations, as described in Williams (1987) (except that Cook's distances are scaled as F rather than as chi-square values).

Cook's distance

1.29 Cook's distance is a measurement of the influence of the ith data point on all the other data points. In other words, it tells how much influence the ith case has upon the model. The formula to find Cook's distance, Di, is the squared error term divided by the product of the number of parameters in the model and the Mean Square Error.

1.30 Using the F distribution to compare with Cook's distance, the influence that the ith data point has on the model can be found. Values in the F distribution table can be used to express the percentage of influence the ith data point has. A percentage of 50% or more would indicate a large influence on the model. The larger the error term implies that the Di is also larger which means it has a greater influence on the model.

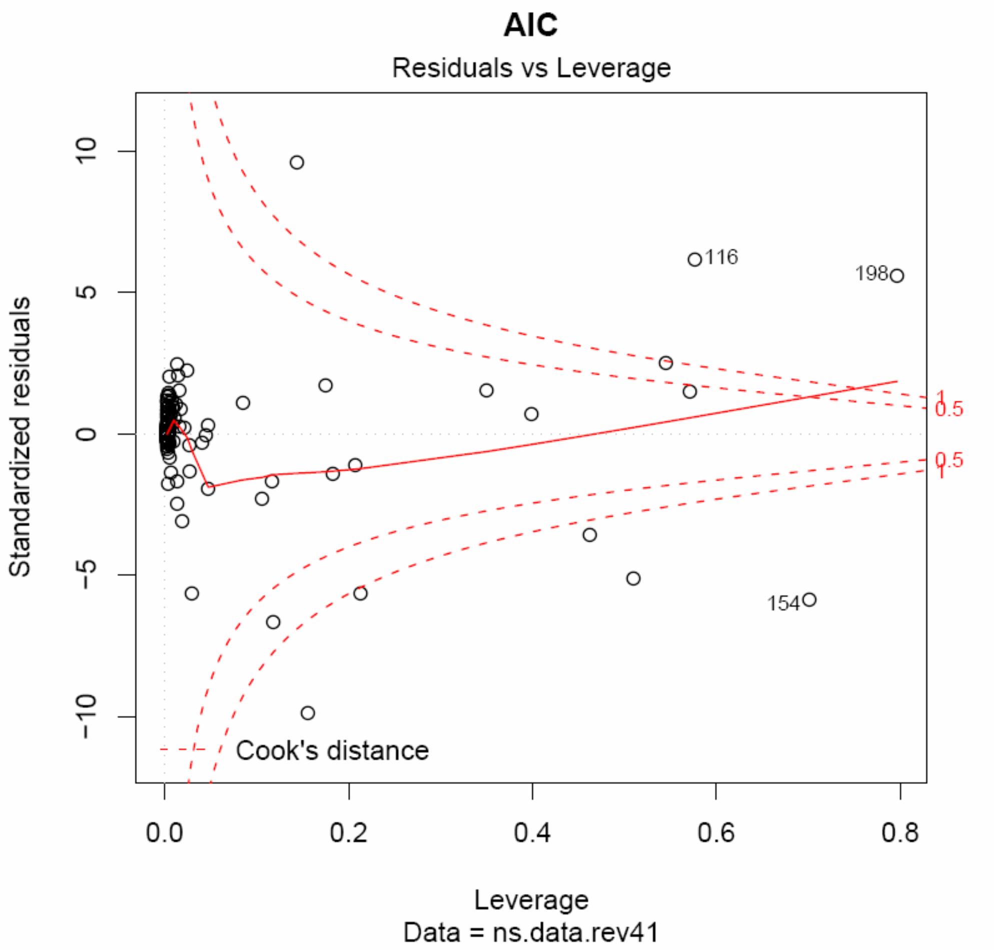

Figure 1-1 Cook's distance test applied to electricity data, low voltage distribution.

DFBETAs

1.31 The DFBETA for a predictor and for a particular observation is the difference between the regression coefficient calculated for all of the data and the regression coefficient calculated with observation i deleted, scaled by the standard error calculated with the observation deleted. The cut-off value for DFBETAs is 2/sqrt(n), where n is the number of observations.

DFFITS

1.32 The DFFITS statistic is a scaled measure of the change in the predicted value for the ith observation. For linear models, the formula is given in a separate document on PP. Large absolute values of Fi indicate influential observations. A general cutoff to consider is 2 or more generally 2 sqrt((number of obs)/number of parameters)

Covariance ratio

1.33 The Covariance ratio statistic measures the change in the determinant of the covariance matrix of the estimates by deleting the ith observation (cf Belsley, Kuh and welsch (1980). The cutoff to consider is 3*parameters/number of observations.

Experimental design

1.34 To assure that the chosen model fulfils the model criteria stated above, in particular with respect to environmental and categorical variables, it is useful to make a set of runs to determine the sensitivity of the model with respect to these parameters. The theory for experimental design and inclusion results for non-parametric methods effectively reduce the necessary runs.

2. Variable selection

Selection criteria for regulatory use

2.01 *Continuity.* In considering the specification of the models, some consideration must be made to the continuity of previous models in the interest of learning and administrative costs for both regulator and firms. In this context, this condition has been expressed as sensitivity analyses on similar datasets to assess the relative benefits from including new information.

2.02 *Robustness*. The model specification and results must be robust to foreseeable cost, technology and institutional changes to guarantee stable incentive provision and minimization of the regulatory risk. Specifications that rely heavily on specific process information, e.g., may become obsolete with technological progress.

2.03 *Verifiability*. An efficiency measurement model used in incentive regulation must be based on verifiable information. Use of poorly defined or private information is directly encouraging opportunistic action. Worse, in yardstick regulation, distorted information may directly affect the incentives of complying firms.

2.04 *Unambiguous*. The model's definitions have to be unambiguous to withstand challenges related to conflicting interpretations, e.g. over time and organizational levels.

2.05 *Output (correlated)*. As discussed at length in Agrell and Bogetoft (2003a) *Dynamic Regulation*, the most robust and least long-run costly regulation regime will be implemented with close definition at the output side and high aggregation on the input side. We pursue this strategy in this report by allocating more effort to the long-run output specification than the (transitional) input problems. The output orientation also yields a process independent model, which strengthens the robustness condition above and creates clear signals of regulatory non-involvement in the operations.

2.06 *Minimal structural impact.* Unless there is a clear and well-founded regulatory agenda related to industrial structure, the model should not give bias to any specific industrial organizational form. In this respect, we refer to a global assessment of the regulatory regime, including the use of the concession instrument and merger control.

2.07 *Feasibility*. A regulatory model must show feasible results for any imaginable outcome to limit regulatory discretion. In incentive regulation, we note the problem of superefficiency, where the DEA program may fail to find an efficiency estimate for certain production profiles. As the superefficiency formulation has some very desirable properties, we will spend some attention to this problem.

Variable specification

2.08 The classification of variables and parameters for the models is illustrated in Figure 2-1 below. With input X or controllable resources we primarily mean the direct costs C(X) for the level or activity estimated (e.g. medium-voltage electricity distribution), but also all variables related to the operating costs and assets deployed, e.g. route length of overhead lines (electricity) and installed power for compressors (gas) The class of outputs Y is made of exogenous indicators for the results of the regulated task, such as typically variables related to the transportation work (energy delivered etc), capacity provision (peakload, coverage in area etc) and service provision (number of connections, customers etc). The class of structural variables Z contain parameters that may have an non-controllable influence on operating or capital costs without being differentiated as a client output. In this class we find indicators of geography (topology, obstacles), climate (temperature, humidity, salinity), soil (type, slope, zoning) and density (sprawl, imposed feed-in locations). However, it is common to find the effects of a particular control in Z correlated with Y and/or cancelled with other controls in Z.

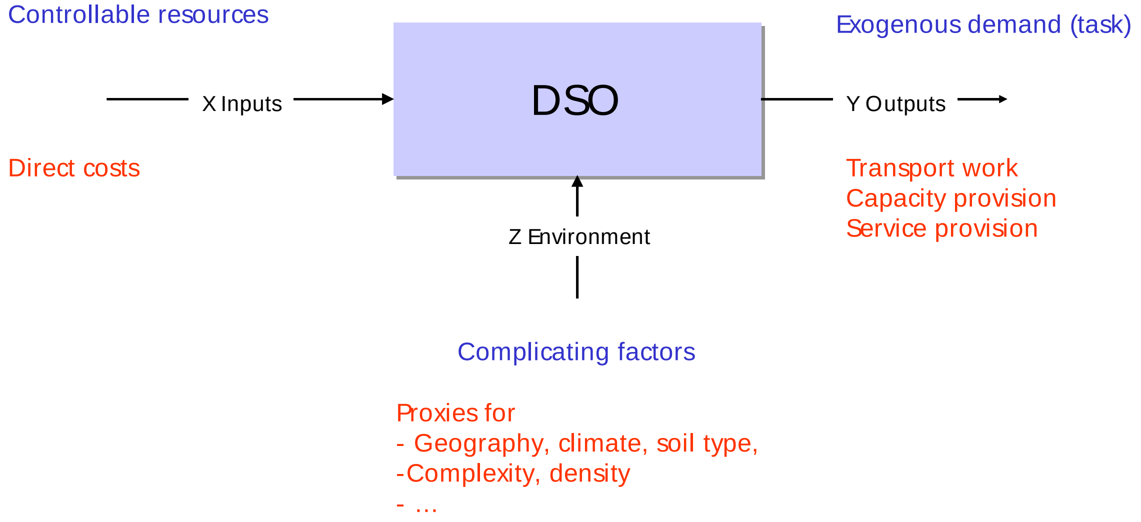

Figure 2-1 Variable classification.

Estimation principles

2.09 The statistical estimation of the benchmarking models is divided into four distinct phases as in Fig X below.

2.10 The first phase investigates the relationship between any resources (controllable variables X) and the resulting costs C(). These models are of limited interest for benchmarking, as the resources are controllable, but serve to validate the data.

2.11 The second phase aims at the validation of the explanation of the intermediate variables (controllable) through the exogenous variables that characterize the service output. These models serve a validation purpose only and to the extent the intermediate variables can be adequately explained by the exogenous variables, they can be omitted from the further analysis, which is a prerequisite for a regulatory application.

2.12 The third phase estimates the cost function as a function of exogenous outputs only, potentially a subset of the variables used in the preceding phase. This step constitutes the core of the benchmarking modeling as it has to be effectuated for each type of model and estimation approach.

2.13 The fourth phase is devoted to augment the model(s) from the third phase with controls (environmental variables) to assure comparability and explain revealed inefficiency. This phase involves the test of a large number of potential candidates for structural variables to determine whether they add relevant information. The phase has in this project lead to the construction and data collection of new variables for e.g. soil type, urban sprawl and age structure of the firms.

2.14 Following the four phases, we have a balanced benchmarking model that is a function of the relevant outputs from the regulated task, subject to the assurance of a structural comparability.

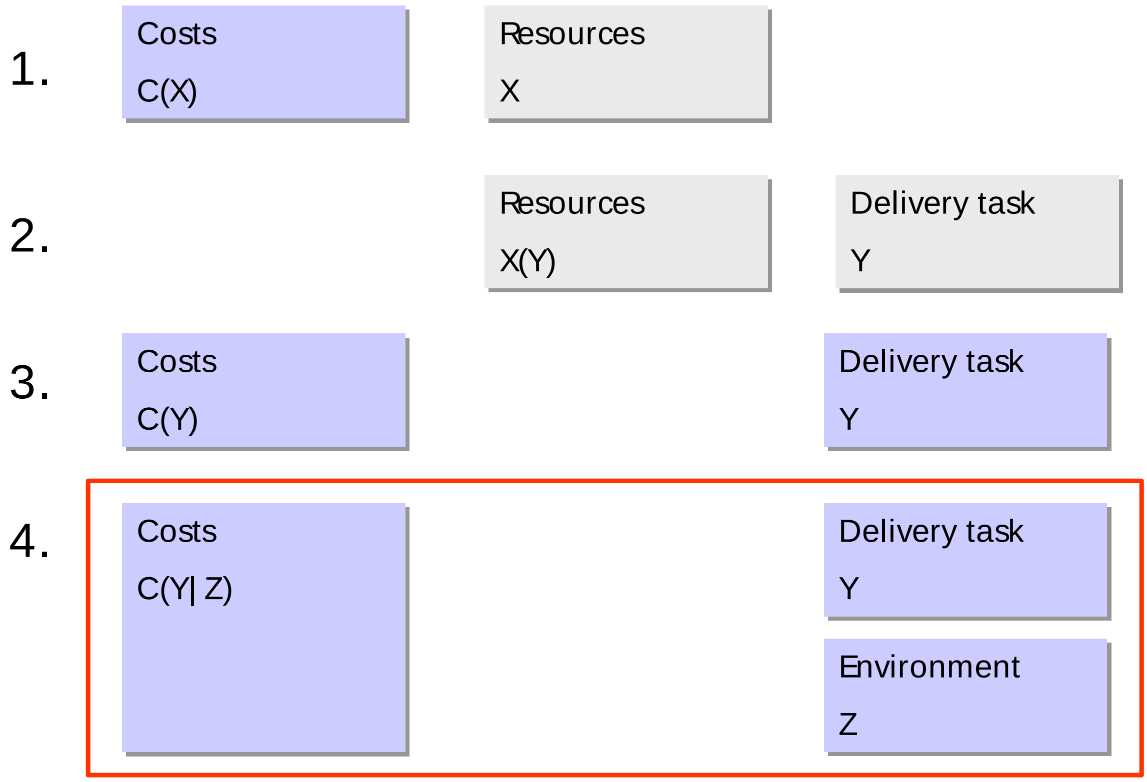

Figure 2-2 Four-stage statistical estimation approach.

T1 Subaddivitity tests

2.15 To give some theoretically sound basis for the selection of the level of aggregation above, we have conducted a test on the subadditivity hypothesis of the underlying cost function. Simply put, a subadditive cost function $C(a,b,\ldots c) < C_1(a) + C_2(b) .. + C_n(c)$ indicates that there is a cost advantage to perform an activity jointly. The test is fairly standard in regulation, cf. Evans and Heckman (1984)[2] when considering e.g. the level of vertical integration allowed in a

---

[2] David S. Evans, James J. Heckman (1984) A Test for Subadditivity of the Cost Function with an Application to the Bell System, American Economic Review, 74(4), pp. 615-623.

natural monopoly. As other European regulators have chosen only two distinguish up to three vertical segments in electricity (TSO, DSO-MV, DSO-LV, including transforming activities) and two in gas (TSO, DSO), we might expect to find support for some integration in electrity

T2 Age effect test

2.16 The age structure of the asset base may potentially have two effects that contradict the two purposes of the benchmarking, the efficiency estimation and the structural comparability.

2.17 First, the incumbent regulation in Germany is cost/input-based which means that the costs and tariffs reflect accounting costs rather than real annuities. Naïve estimations of cost efficiency of firms at different stages in the investment cycle would result in the infeasible finding that firms ideally should remain in the state with assets (almost) fully depreciated. To correct this problem, the impact of an age-corrected capital measure must be employed.

2.18 Second, as has been hypothesized for e.g electricity TSOs, asset age may have an unfavorable impact on operating cost. Although not an issue under annuity pricing, this may disturb the comparability of firms using different activation policies.

2.19 The age effect test T2 is defined as the construction of weighted asset age parameters.

2.20 In gas, the asset ages are estimated from the given proportion of pipelines in age classes, weighted with the proportion of lines (in km), cf. Figure 2-3 below.

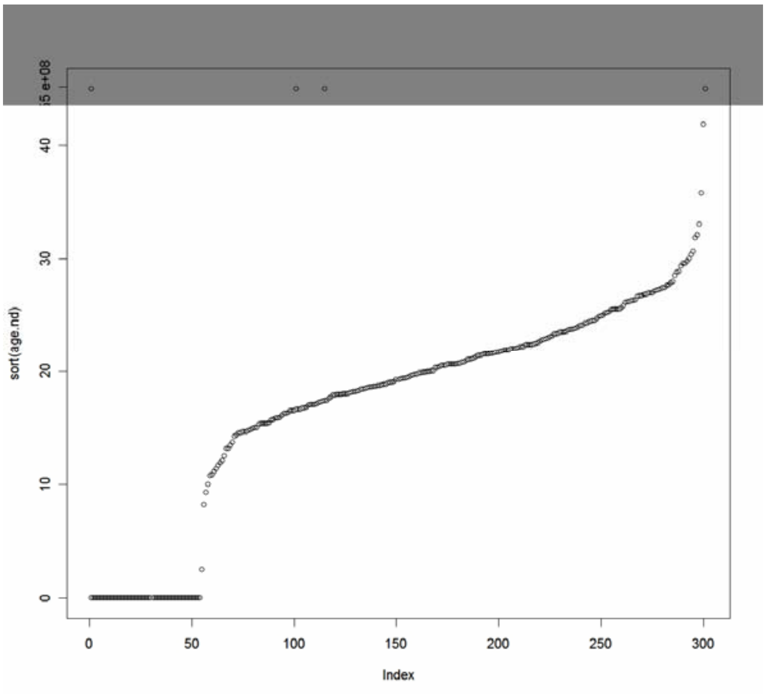

Figure 2-3 Example of age estimator: average age for low pressure gas pipelines

2.21 For electricity, an asset age parameter was constructed from the proportion of residual book value (depreciated) to total (non-depreciated) book value for five asset classes. The underlying assumption is that the firms practice linear depreciation.

2.22 The asset age estimators have been included as potential explanatory variables in class Z to determine whether age has a impact on (i) cost, (ii) uncorrected efficiency estimates under DEA and SFA.

T3 Capex-opex tests

2.23 In order to further investigate the impact of capital vs. operating cost differences, to potentially control for incumbent inefficiency in capital rather than in operating expenditure, it is desirable to run decomposed short-run and long-run model to determine these effects. This test has been postponed due to a limited dataset and some incompatibilities between databases.

3. Model structure

3.01 Below we outline and motivate the principal structure of the benchmarking models for both electricity and gas.

Definitions

3.02 A benchmarking model is a quantitative representation of the relationship between resource consumptions (*input*) and the supply of demanded services (*output*) based on a set of comparable observations.

3.03 The model is used to estimate *cost efficiency*, defined as the ratio of actual cost to minimal cost to produce an equal or higher amount of products and services under equal or more severe environmental conditions. The minimal cost calculated by the benchmarking model for each output profile and structural specification is said to be the *efficient cost* for that condition.

3.04 To enable application of the efficiency concept in regulation, i.e. to obtain feasible and realizable targets, two conditions have to be fulfilled: (i) minimal extrapolation from the data and (ii) minimized data error.

3.05 Based on the definitions above, we may already infer certain important properties of a benchmarking model for use in e.g. incentive regulation.

Output orientation

3.06 Although a detailed input description, i.e. inclusion of resource variables such as the type of assets deployed, the number and qualification of staff employed, and the type of costs incurred in the operations, may bring interesting information to managers, the previously discussed endogeneity makes the model useless for incentive provision. In fact, a too detailed input description not only limits the incentives that a regulator can put on the results, but it may also misinform firms about the true latent efficiency potential by introducing artificially high substitution costs between inputs in the benchmarking. Modern incentive-based regulation is output-based, meaning that the input side is characterized by maximal aggregation to permit the firm to realize any beneficial substitutions, and that the effort in modelling is invested in finding good indicators for the services really demanded and delivered by the final customers. All intermediate steps are seen as internal processes that the regulatory benchmarking model has no interest to measure or influence, only their final impact on cost matters to the efficiency estimation.

3.07 Which are then the relevant output dimensions in energy networks in general? Customer tariff calculations can not be directly used, as until now they have been based on accounting costs for the activities. The dimensions are instead found by a purely logical reasoning. In the liberalized market, the final client buys his energy from a supplier in an open competition. To exercise the purchase the client turns to a system operator and requests a seamless and uninterrupted transportation and distribution of the energy from the supplier to the connection point. This creates three service dimensions for the distribution task; *transportation work*, *capacity provision* and *customer service*.

3.08 In electricity, the volume transferred gives rise to physical losses that are proportional to the network configuration, the distance between supply and connection and the outside temperature. In gas, the volume transported also relates to the energy costs for pressurizing the network. This dimension, which is perfectly measurable at final client level, is called *transportation work.* The relevant variables in our dataset include total delivered electricity (MWh) per voltage level, measured or non-measured, as well as the total energy contents in the gas delivered (MJ) or the gas volume delivered (nm^3). For gas, the normalized volume has been retained, rather than the energy contents, as the difference in the two is related to e.g. temperature and quality that are not relevant for the costs of the gas distributor, but related to the final use.

3.09 The demand from the client for electricity connection cannot be refused under the Universal Service Obligation (USO) and the client is not contractually requested to remain connected, or to guarantee any specific load profile. In gas, we note moreover that the client has the right *not* to be connected, even if the network extends to his house or property. USO is a great privilege, but as there are no free privileges, the corresponding obligation of the system operator to foresee, provide and adjust the capacity of the network to the demand carries a cost that corresponds to the *capacity provision* the client enjoy. In this dimension we find variables that help to explain the dimensioning, the capacity utilization and thus also the economies of scale in the networks. In our dataset, we may mention coincidental and non-coincidental peak load (MW) per voltage and transformer level, peak feed and outtake rates (nm^3/h), but also the delivery area itself ($km^2$2) and its population are USO drivers for capacity provision.

3.10 Once connected, the customers require both specific capital assets (meters, connections, lines and cables, transformers, compressors) with their associated direct and indirect costs, in addition to some direct operating costs (connection, metering, billing, fault detection and correction, disconnection, inspection). We label all these connection point proportional services as *customer services*. Relevant variables in our data to capture this dimension are the number of metering points per voltage and transformer level and the number of customers per pressure, voltage and transformer level. Alternative variables used in regulation include the number of connection points per voltage and pressure level and the number of terminal blocks in gas.

3.11 The output side of the model should adequately represent the three service dimensions. The selection of the exact parameters within dimension and their functional form is left to the extensive statistical tests reported elsewhere. The core model is estimated prior to the selection of structural correction parameters.

Structural correction

3.12 Comparability between operators with the same output profile, but different costs, is assured through the successive test of plausible structural parameters on the results of the previously estimated core model. The candidates are selected among indicators for particular operating contexts that are likely to significantly deviate from that of the firms ranked efficient by the core model. In our datasets, we have solicited, constructed and used indicators for asset age and profile, slope, soil type (electricity), joint operation of other utilities and historical load growth patterns (gas). All tested variables have been documented and their capacity to explain cost deviations has been recorded. The choice to include or not a significant structural correction factor has been made using information-criteria from statistical theory. Some details of the tests in this respect are found in this report.

Integration

3.13 The network distribution of energy can be modeled by two principally different approaches with regard to structure: the separable model and the integrated model.

3.14 The vertically separable model (Fig 4-1) is based on separate estimations of cost functions and corresponding efficiency assessments for each vertical level, e.g. medium voltage distribution of electricity. Costs from superior levels are regarded as uncontrollable and no consideration is made to the joint ownership and/or operation of multiple vertical levels. As the choice of variables can be tailor made for each vertical level, a high fit can usually be achieved.

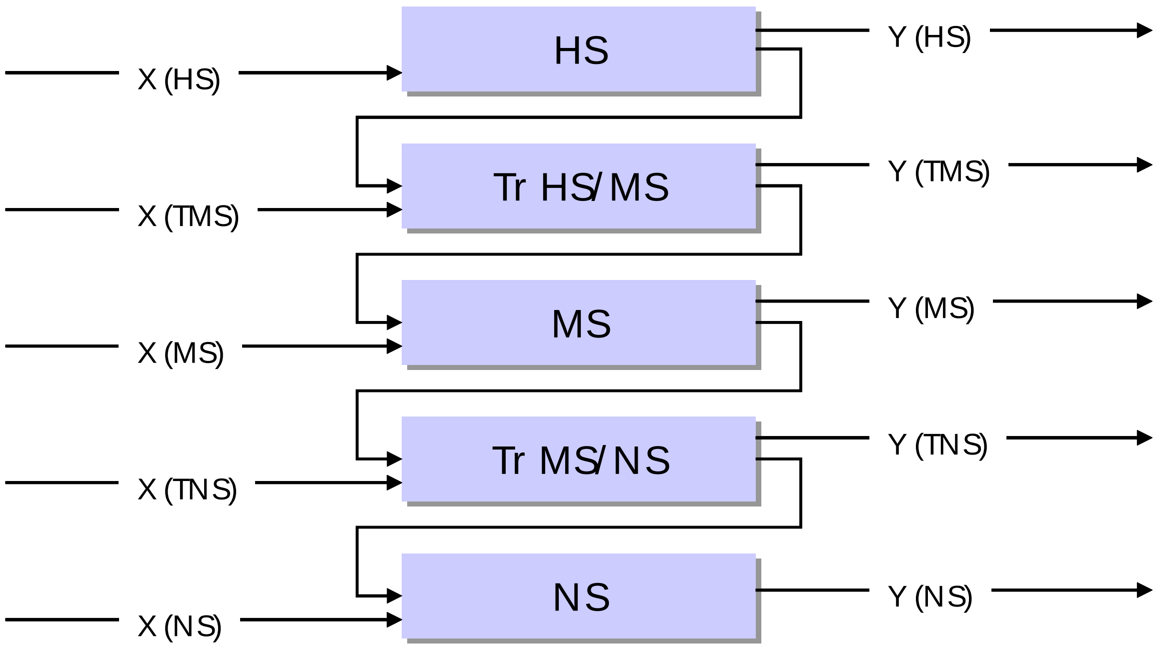

Figure 3-1 Separable model (example electricity distribution).

3.15 The integrated model (Fig 4-2), however, gives a more aggregated perspective on the activity as to take into account the synergies between vertical levels. Thus, internal monetary and energy flows are ignored as the integrated system is benchmarked. As all enterprises do not share the same vertical segments, the resulting model will have to select a set of variables that adequately characterizes all firms. The advantage is a greater stability to "accounting creativity" in regulated firms and an explicit recognition of the expected integration synergies.

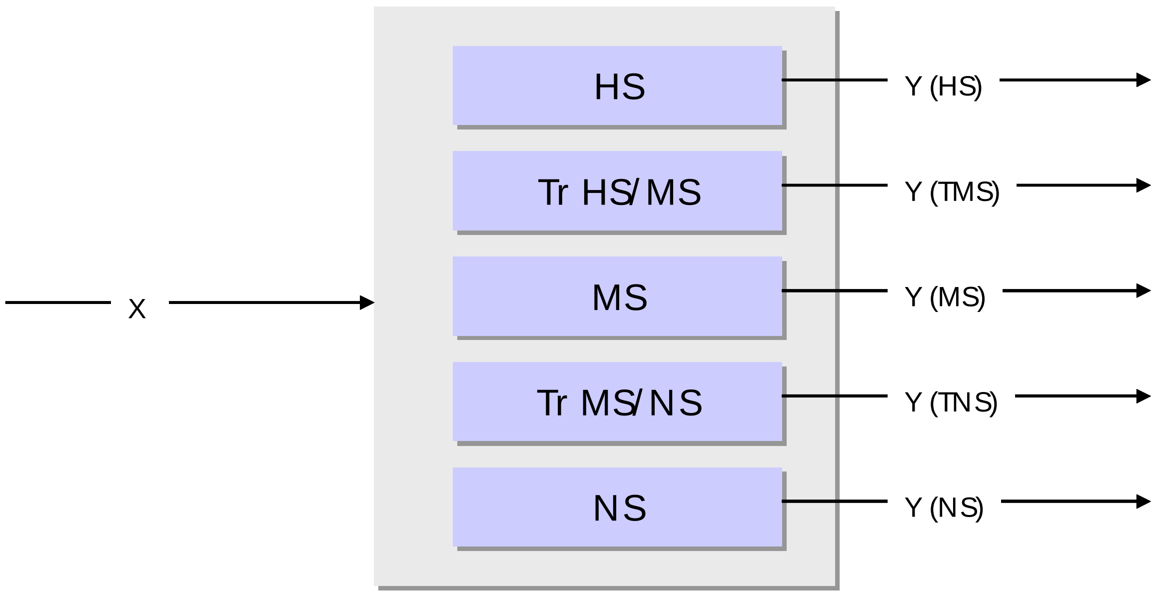

Figure 3-2 Integrated model (example electricity distribution).

Summary

3.16 Our approach for regulatory benchmarking to support incentive regulation is based on the concept of a core model with an aggregated input specification, here total direct cost less taxes and a detailed output specification along the final client dimensions transport work, capacity provision and customer service. The core model is augmented with environmental variables when they are shown to significantly explain cost deviations using both statistical and analytical techniques. The scope of the core model should correspond to the economies of scale and scope in the real operations, as to reduce model complexity and diversity, to avoid distortions due to bias in number of observations and model specification, and to acknowledge operating synergies rather than accounting creativity in the efficiency calculations. In the current dataset we have found support to use models that are integrated from low voltage up to high voltage for electricity and completely integrated in gas.