NVE
Reguleringsmyndigheten
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# RME EKSTERN RAPPORT

Nr. 3/2021

# Variables for measuring the task of supplying reliability in the distribution grid

*Thema Consulting Group*

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| **Redaktør:** | Tore Langset |
| **Forfatter:** | Thema Consulting Group |
| **Forsidefotofotograf:** | Ole-Petter Kordahl (fotokollasj) |

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**Sammendrag:** THEMA har på oppdrag fra RME studert hvordan oppgaven med å levere god og sikker strømforsyning kan måles og uttrykkes som en variabel i effektivitetsanalysene. Omfanget av oppgaven vil blant annet være avhengig av hva slags kunder som nettselskapet skal levere til. Forskjellige kundegrupper vil ha varierende ulemper og kostnader ved et strømbrudd, og vil derfor også ha ulik betalingsvillighet for å unngå avbrudd. Et annet forhold som kan påvirke oppgaven med å levere pålitelighet er kundenes geografiske plassering i nettet. THEMA drøfter hvordan en oppgavevariabel kan defineres med utgangspunkt i disse observasjonene.



**Emneord:** Inntektsramme, nettselskaper, økonomisk regulering, effektivitet, leveringspålitelighet, reliability, KILE, eksogene oppgavevariabler



Reguleringsmyndigheten for energi
Middelthuns gate 29
Postboks 5091 Majorstuen
0301 Oslo

Telefon: 22 95 95 95
E-post: rme@nve.no
Internett: www.reguleringsmyndigheten.no



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# Forord

Reguleringsmyndigheten for energi (RME) regulerer nettselskapenes inntekter. Formålet er å bidra til effektiv drift, utnyttelse og utvikling av nettet. RME gjennomfører hvert år en effektivitetsanalyse som måler selskapene mot hverandre, og rangerer dem ut fra hvor mye ressurser de bruker på å bygge, drifte og vedlikeholde nettinfrastrukturen. Nettselskapenes avkastning bestemmes deretter av hvor kostnadseffektivt de løser sine oppgaver.

En av de sentrale oppgavene til nettselskapet er å tilby en god og sikker strømforsyning til sine kunder. Dette kaller vi leveringspålitelighet. Omfanget av denne oppgaven vil blant annet være avhengig av hva slags kunder som nettselskapet skal levere til. Forskjellige kundegrupper vil ha varierende ulemper og kostnader ved et strømbrudd, og vil derfor også ha ulik betalingsvillighet for å unngå avbrudd. Dette er kartlagt i den eksisterende KILE-ordningen. Et annet forhold som kan påvirke oppgaven med å levere pålitelighet er kundenes geografiske plassering i nettet. Vi vet blant annet at sannsynlighetene for avbrudd øker når kunden befinner seg langt fra et innmatingspunkt.

Med kunnskap om kunders betalingsvillighet og hvor kundene befinner seg i nettet, ønsker RME å utvikle nye variabler som beskriver oppgaven med å levere pålitelig strømforsyning. Formålet er ikke å finne det optimale eller riktige nivået på leveringspålitelighet, men å definere oppgavevariabler som kan brukes i en fremtidig effektivitetsanalyse.

Vi har engasjert THEMA til å se på dette, og i denne rapporten publiserer vi arbeidet deres. Alle vurderingene og konklusjonene i rapporten er konsulentenes egne.

En referansegruppe bestående av Glitre Nett, Jæren Everk, Klepp Energi og Mørenett har bistått med bransjekunnskap og data som har blitt brukt for å verifisere metodene. Vi er takknemlig for den innsatsen disse selskapene har bidratt med i prosjektet. Selskapene har imidlertid intet ansvar for konsulentens konklusjoner

Vi inviterer alle til å komme med innspill til arbeidet innen 15. mars 2021. Tilbakemeldinger merkes med referansenummer 202100557 og sendes til rme@nve.no. Vi tar med oss THEMA sitt arbeid og innspill på dette i det videre arbeidet med reguleringsmodellen.

Oslo, januar 2021

Ove Flataker

Ove Flataker
direktør
Reguleringsmyndigheten for energi

Langset

Tore Langset
seksjonssjef

# Variables for measuring the task of supplying reliability in the distribution grid

THEMA
CONSULTING GROUP

## Project info

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## About the project

This report investigates alternative output parameters for the DEA model in Norwegian DSO income regulation. It attempts to define a customer's demand for reliability and integrate it into a variable that describes the related task of grid companies. Different variables are introduced and discussed.

## Project team

**Project manager**
Åsmund Jenssen, Lisa Zafoschnig

**Contributors (alphabetically)**
Haavard Holta
Sigmund S. Kielland
Stephany Paredes
Berit Tennbakk

# Executive Summary

## Background and problem statement

The Norwegian Energy Regulatory Authority (Reguleringsmyndigheten for Energi, RME) is responsible for regulating the income for Distribution System Operators (DSOs). The so-called Data Envelopment Analysis (DEA) benchmarking model evaluates the performance of each grid company based on a number of indicators and determines the allowed income based on the resulting relative efficiency and the company's actual annual cost. Current output parameters in the DEA model are the number of customers, the total length of lines and the number of substations in the high-voltage distribution grid. As more data is made available from smart-meters and centralised infrastructure databases, new output parameters for the benchmarking process can be considered. Ideally, such parameters should represent the task of the DSO (not its effort) and provide incentives for efficient grid reinforcement while being highly exogenous, comparable and easy to compute from available data. In the current benchmarking model, the customer cost of outages (CENS, Cost of Energy Not Supplied, or KILE in the Norwegian terminology) is part of the total costs on the input side of the model. However, the model does not take into account differences between grid areas with respect to customers' different demand for reliability and different probabilities for outages. In short, the task of supplying reliability is not represented on the output side of the model.

On this background THEMA has been commissioned by RME to analyse how the task of supplying reliability can be included in the DEA benchmarking model for distribution grids. For this purpose, we have carried out a qualitative analysis of different aspects of the demand for reliability and related costs, and a quantitative analysis using actual grid data and customer data from four Norwegian distribution grids.

## A reliability variable must fulfil several criteria

By using stylised example grids, insights from economic theory and empirical research into the costs of outages, we have developed a set of criteria that the reliability variable should reflect, specifically differences in the demand for reliability in different customer groups, the probability of an outage, and economies of scale.

**Demand for reliability** in different customer groups. The CENS functions used by RME to calculate the regulatory outage costs show that the cost of outages varies significantly per kW and time unit for different customers. The value of avoiding an outage in e.g. power-intensive industries and the commercial sector is much higher than for households. These differences also impact the economic value of measures in the grid to avoid outages depending on the customers affected.

**The probability of an outage,** particularly linked to distances in the grid. The longer the distance between a transformer and a substation, or between a substation and an end-user, the more likely it is that a fault will occur and cause an outage.

**Economies of scale.** As the grid is a natural monopoly, and there will be economies of scale with respect to reliability. On an abstract level, this means that the cost of supplying two units of reliability will be less than the double of the cost of one unit.

In addition, the output variable should be *exogenous* and easy to compute in practice. That the variable is exogenous, means that the network companies should not be able to influence the value of the variable. By easy to compute we mean that the variable can be calculated using available data from the network companies and without undue processing time.

In practice, the task of delivering reliable power is also affected by other factors such as adverse weather conditions. In the current DEA model, geographical framework conditions are not included. Instead the DEA results are corrected at a second stage using statistical methods to adjust the results for the impact of geographical factors. Thus, we have not looked at geography factors in the present analysis.

## The Value of Energy based on CENS functions is the starting point

The key building block of the analysis is an exogenous measure for the customers' willingness to pay for reliability. This measure captures a key part of the task of providing a reliable power supply, namely the demand for reliability from different customer groups. The demand for reliability is independent of the grid companies' decisions and purely a function of the consumption characteristics, e.g. the economic cost of outages for the customers due to lost production, absence of lighting and heating, loss of data and communication services, damage to equipment etc.

For that purpose, we use the CENS functions as a starting point. The CENS functions are based on research into the *Value of Lost Load* (VoLL) for different consumer groups. However, to estimate the demand for reliability, we do not use the CENS functions directly. Instead, we define the parameter *Value of Energy* (VoE). VoE is simply the weighting of power consumption with the corresponding CENS functions per customer group and the relevant adjustment factors for weekday, season, time of day, etc. By using this method, consumption in e.g. the commercial sector will have a greater weight than e.g. household consumption. The intuition behind the method is that customers with a high VoLL will also have a high value of the energy that is actually delivered and hence a higher demand for reliable power supply compared to customers with a low VoLL. This higher demand for reliability will in turn increase costs as the grid company will have to take more measures to reduce the risk of outages.

## A separate variable for reliability is the best way forward

In the analysis, we have considered two main sets of options.

The first option is to integrate a parameter reflecting the demand for reliability into the existing DEA output variables (number of substations, number of customers and total line length) or some potential new output variables (e.g. the so called power distance variable). These integrated variables can be calculated simply as the product of the reliability measure and the value of the relevant output variable. We have chosen to base this demand for reliability parameter on the Value of Energy concept, as defined above.

The second option is to define a separate variable to reflect reliability, either distance-independent or weighted with distance (reliability distance). The distance-independent variable can be calculated as the Value of Energy without further adjustment. The reliability distance can be calculated using an algorithm developed for the power distance variable that has been investigated in a separate project, substituting power consumption per hour with the Value of Energy.

We have analysed the six options mentioned above with the data from the four grid companies. The results show that there are significant differences between the companies depending on the specification of the model. The main difference is between the reliability distance on the one hand and the other five variables on the other. The reason is that the Value of Energy enters directly into the integrated variables and the distance-independent variable and they are thus highly correlated.

Based on the evaluation of the different options according to the criteria we have used, we conclude that the reliability distance (distance-weighted demand for reliability) is the most suitable option. This variable reflects both the demand for reliability and the distance-related probability of outages, and it is to a large degree exogenous.It is also not too complicated to compute.

The reliability distance can also be tailored to reflect economies of scale with respect to the supply of reliability. However, further work should be done in order to understand the economies of scale with respect to reliability. The choice here can have a significant impact on the ranking of grid companies.

The distance-independent demand for reliability could also be an option. RME should investigate in more detail how distances in the grid actually impact the probability of outages to determine whether it is desirable to include distance in the reliability task variable. If that is the case, it is an argument in favour of the reliability distance. The distance-independent demand for reliability also requires further analysis of how economies of scale affect the measure.

The integrated variables do not reflect economies of scale apart from the reliability-weighed power distance, which uses the same underlying scale assumptions as the power distance variable. In principle it is possible to account for economies of scale, but it is not straightforward how it should be done. The variables also differ with respect to exogeneity. With the exception of the reliability-weighted power distance, they also do not reflect the probability of outages due to distances in the grid. As noted above, this is an issue that requires further analysis.

In any case, we also recommend that RME looks into the baseline for calculating the Value of Energy, e.g. the duration of outages used for ranking different customer groups and the role of the adjustment factors.

Including a separate variable for reliability can reduce the incentive power of the benchmarking model. The choice of the number of variables is however an assessment that RME must make based on their views of the full model, including the geography correction.

# Contents

# 1. Introduction

The Norwegian Energy Regulatory Authority Reguleringsmyndigheten for Energi (RME) is responsible for regulating Norwegian electricity network companies (Distribution System Operator (DSO)[1]). A key element of the regulation of distribution grids is RME's Data Envelopment Analysis (DEA) model. RME's DEA models are designed to benchmark the costs of a network company given a set of outputs that describe the tasks of the given company. In the distribution grid, the outputs are the number of customers, kilometres of lines and the number of substations[2] in the high-voltage distribution grid [3]as proxies for customer demand for each DSO.

RME is now exploring the possibility to replace the existing output measures by exogenous measures that better reflect the task of grid companies. In previous work we have analysed inclusion of the electric power distance as a parameter that considers the transferred power and the distance to each demand node. An additional aspect of a grid company's task is the reliability of power supply, i.e. the continuity and quality of supply provided to different customer groups. In this report, we analyse the possibility to introduce an output variable that reflects the demand for reliability in the DEA model.

## 1.1. DSO income regulation

In Norway, the allowed income of grid companies is determined based on a revenue cap. In aggregate, the costs incurred by all grid companies are covered by the revenue caps but the regulation aims to reward the most efficient companies with higher income to create incentives for operational improvement and socioeconomic investments. The benchmarking of efficiency is performed using the DEA model which compares grid companies against another to determine which DSO is most cost efficient in fulfilling its task. The idea behind the design of the regulation is that each grid company incurs comparable costs in solving their tasks.

The total allowed income of each grid company, and thus how much income each grid company can collect from their customers via grid tariffs, is defined by

$$TI_t = IR_t + E_t + KON_t + FoU_t - KILE_t + TE_t, \quad (1.1)$$

where $IR_t$ is the revenue cap (Norwegian: *inntektsramme*), $E_t$ is the ownership tax, $KON_t$ is the cost of tariffs to higher grid levels (regional and transmission grids), $FoU_t$ are expenses for research and development subject to special approval, $KILE_t$ are the costs of energy not supplied (CENS) and $TE_t$ is an adjustment to remove the time lag for capital costs.

In this report we focus on the aspect of security of supply in income regulation. Currently reliability is reflected through CENS as a direct reduction in allowed income and in the revenue cap where CENS is part of the input to the cost base.

The revenue cap constitutes the most important component of the allowed income and is calculated as

$$IR_t = (1 - \rho) \cdot K_t + \rho \cdot K_t^*, \quad (1.2)$$

where $K_t$ is the company's actual costs also re-

[1] The Norwegian term *nettselskap* is translated to grid company or DSO in this report.

[2] In this report we use *substation* to refer to the Norwegian *nettstasjon*, i.e. a transformer station from the high-voltage (10 to 22 kV) distribution grid to the low-voltage (220 to 400 V) distribution grid.

[3] high-voltage refers to a voltage level of 1 to 22 kV in the Norwegian distribution grid. In this report we will use *high-voltage* and *low-voltage* (220 to 400 V) according to Norwegian grid standards.

ferred to as cost base, $K_t^*$ is the cost norm, and $\rho$ is a factor defining the share of the income of a grid company from the cost norm. The cost norm is set using the DEA benchmarking model. If a company is an average company (100 % efficient post calibration of cost norms compared to expected costs), $K_t = K_t^*$. If the company has an efficiency above 100 %, then $K_t \geq K_t^*$, implying a higher rate of return than the RME interest rate. A less efficient company will have a rate of return that is lower than the RME interest rate. Currently, $\rho$ is set to 60 %, meaning that 40 % of the cost base can be directly passed on to consumers, while 60 % is based on the benchmarked cost norm. In short, the average company is classified as 100 % efficient, while the most efficient companies are above 100 % and less efficient companies have an efficiency below 100 %.

Both the cost base and the cost norm are related to the actual costs incurred by each grid company. The cost base is defined as

$$\begin{aligned} K_t =& (DV_{t-2} + KILE_{t-2}) \cdot (KPI_t / KPI_{t-2}) \cdot NT_{t-2} \cdot P_t \\ &+ AVS_{t-2} + AKG_{t-2} \cdot r_{NVE}, \end{aligned} \tag{1.3}$$

where $DV_{t-2}$ are the operation and maintenance costs two years ago, $KILE_{t-2}$ are CENS from two years ago, $NT_{t-2}$ are grid losses from two years prior, $P_t$ is the reference power price in the given year, $AVS_{t-2}$ is the return on investments and $AKG_{t_2}$ is the asset base which is based on existing assets and multiplied with the reference rate of return $r_{NVE}$ defined by Norges Vassdrags- og Energidirektorat (NVE). The cost norm is calculated as

$$K_t^* = \eta \cdot K_t + T_c, \tag{1.4}$$

where $\eta$ is the efficiency resulting from the DEA benchmarking, $K_t$ is the cost base and $T_c$ is an addition resulting from the re-calibration of the cost norm due to geographical and climatic conditions.

### 1.1.1. DEA benchmarking model

The DEA model is used to compare grid companies against another and determine their relative efficiency in fulfilling their task. The task of the grid company in the distribution grid is currently represented by the following output parameters:

- number of customers
- number of substations
- kilometres of lines in the high-voltage distribution grid

As a grid company is evaluated on how cost efficiently it covers its tasks, it is important that the output parameters describe the task – or the cost drivers – of the grid company in a relevant way. The task is to cover the demand of all customers at all times, and the main costs drivers are investment costs (CAPEX), operation costs (OPEX) such as cost of delivering power and cost of losses, O&M costs, and administrative costs.

### 1.1.2. Reliability in the income regulation

The Norwegian income regulation accounts for reliability through the cost of energy not supplied (CENS, Norwegian KILE, *Kvalitetsjusterte inntektsrammer ved ikke levert energi*). CENS is calculated for each outage based on CENS factors for the affected customer group, the time and duration of the outage and the affected power. The functions to determine the cost of each outage are defined in [1]. Figure 1.1 illustrates the specific outage cost for the six main customer groups depending on the outage duration.

CENS enters the calculation as a deduction from the total allowed income and as part of the cost base in the revenue cap. Thereby, the socio-economic cost of an outage is reflected as part of operational costs of each grid company. Low security of supply will penalise grid companies with higher CENS, resulting in lower allowed income.

In the DEA model, CENS costs are part of the input, i.e. the output variables are compared to the

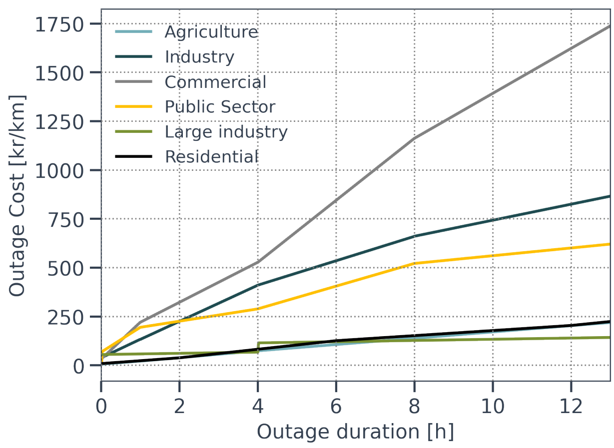



**Figure 1.1.:** *Specific outage cost as a function of outage duration for different customer groups [1].*

total cost of each grid company which includes the cost for energy not supplied. On the output side of the DEA model, reliability is currently not directly reflected as part of a grid company's task.

## 1.2. Data processing

For the computation of the value of energy presented in later chapters, we were provided with data from four Norwegian grid companies. The data was pre-processed and standardised by Multiconsult. In the following sections we give a brief overview of involved stakeholders, their roles and the provided data.

### 1.2.1. Involved grid companies

Four grid companies comprised the reference group for this project. Their role was to provide data from their license area and offer input to the proposed methods. The involved DSOs were

- Mørenett
- Glitre Energi Nett
- Jæren Everk
- Klepp Energi

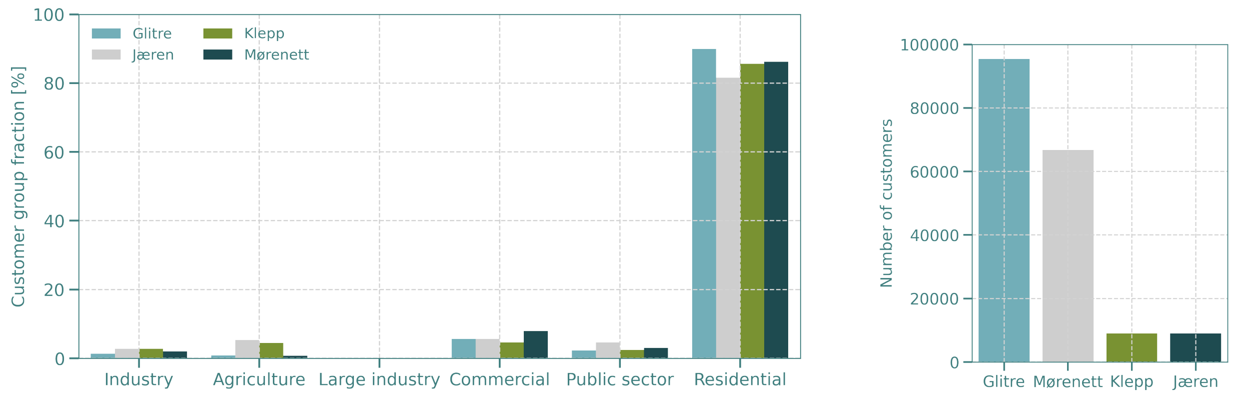
These four DSOs also cover different geographies. Both Klepp and Jæren are located in a coastal area, and differ in that Jæren has a high amount of high-voltage 400 V lines in its grid. While Mørenett also spans a coastal region, there is an even higher amount of fjords and mountains in this grid area. With a grid area containing fjords, the inclusion of Mørenett helps to identify special considerations for challenging geographical conditions. Glitre on the other hand is situated inland, and also contains larger urban areas like Drammen.

The size of the four grid companies vary from roughly 95 000 to 9 000 customers, as seen in Figure 1.2b. Glitre has the greatest number of customers, whereas Jæren has the fewer customers. Klepp and Jæren have approximately the same number of customers, but vary in what type of customers are present. Both Jæren and Klepp have a high percentage of industrial and agricultural customers but Jæren has more public sector and commercial customers. Residential customers is the most common customer type for all grid companies, and the relative ranking between the grid companies also follows the size of the grid companies. In other words, Glitre has the highest number of customers, and also the highest fraction of residential customers. Jæren has the fewest number of customers, and also the lowest fraction of residential customers.

It must also be noted that the four included DSOs form the basis for the empirical work outlined below. These DSO represent only a small fraction of the DSOs in Norway, and is not a representative set of all DSOs in Norway. The data from the DSOs in this study therefore provides a basis for analysing the results, and to point out general trends. There might be peculiarities for other DSOs that are not captured by the analysis in this report.

### 1.2.2. Data provided

The four grid companies in the reference group each provided the following raw datasets used in this project:




**(a)** *DSO customers divided into customer groups.*

**(b)** *Number of customers, (DEA 2019).*

**Figure 1.2.:** *Number of customer and customer groups.*

**Metering point metadata:** Geographical information on location of metering points, customer types and metering point IDs.

**Substation metadata:** Geographical information on location of substations and transformers linked to substation IDs.

**Metering data:** Hourly meter readings for all metering points covering a full year from March 2019 to March 2020.

**Outage data:** Data on occurred outages in the reference year linked to metering point ID, time and duration of outage.

The three datasets were processed and standardised by Multiconsult, as described in [2]. Coordinate data was then transformed from WGS84 to UTM32. The latter is a two-dimensional projection, where the direct distances between points can be calculated.

After receiving the standardised datasets, the data was further pre-processed and used as input for the algorithms presented in this report. All programming was done in Python, making use of the data handling packages Pandas and numpy. Geopandas, shapely and pyproj were used for handling of geographical data.

# 2. Reliability in international benchmarking models

In the following section, we review a selection of the literature on benchmarking of electricity networks to see how the demand for reliability has been treated in other benchmarking models. For this, we elaborate on the examples of Sweden, Denmark and Spain.

## 2.1. Sweden

In Sweden, the benchmarking model is based on a combination of historical and mathematical considerations for each DSO. The regulatory period is four years, where a new regulatory cap is determined for the DSOs. This is determined by the National Regulatory Authority (NRA) in Sweden, the Swedish Energy Markets Inspectorate (Energimarknadsinspektionen, Ei).

The incentives for ensuring sufficient reliability of supply is a combination of rewards and penalties related to the performance relative to the individual baselines. For each DSO, baselines are calculated for different metrics. These baselines are based on both historical levels of that specific DSO, and a comparison with other DSOs. The baselines are further calculated from the total number of outages, and the total outage time. These metrics are considered by System average interruption frequency index (SAIFI) and System average interruption duration index (SAIDI), respectively. Even though all interruptions are reported, interruptions where DSOs must pay a fine are not included in the revenue cap, to avoid double counting. An example of this is interruptions longer than 12 hours, since these interruptions are subject to individual economic customer compensation.

Further, in addition to purely considering the number of outages and outage durations, customer groups and customer density is also considered. Customer groups are similar to the Norwegian customer groups used for Cost of Energy Not Supplied (CENS), however only considering industry as a single customer groups, rather than specifically handling energy-intensive industry. The customer density is the number of customers per km power line, which constitutes an output for the company-specific baseline.

Both the customer density adjustments and the key metrics SAIFI and SAIDI are considering the entire area of the DSO and will therefore not be able to pick up deviations in the reliability of supply within the specific system. To overcome this, the NRA has introduced another metric considering Customers Experiencing Multiple Disruptions ($\mathrm{CEMI}_n$). This metric includes the number of customers experiencing $n$ or more disruptions. The quality of supply is considered good for $n < 4$, and therefore $\mathrm{CEMI}_4$ is used together with SAIFI and SAIDI to benchmark the reliability of supply.

The customer density is used as an input in the benchmarking model in Sweden. Here, the performance of the individual DSO is adjusted relative to the customer density, such that DSOs with equal customer density will get the same baseline of required reliability of supply. Further, the customer density is categorised into one of three categories, where the grid characteristics are classified as either rural, mixed or urban grid. For these categories, the customer densities are <10, between 10 and 20, and >20 customers per km power line, respectively. The average performance of the Swedish DSOs is found from the benchmarking, where the output from the benchmark

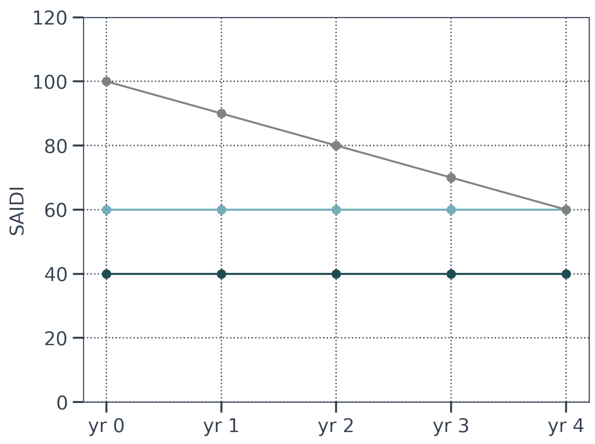



**Figure 2.1.:** *Baselines for average performance, underperforming and overperforming DSO.*

is a baseline for the three metrics. Further, to incentivise DSOs with better achievements than the average baseline to maintain a high reliability, separate baselines are calculated for overperforming DSOs. In reality, the baselines for the overperforming DSOs are taken from their historical performance, thereby encouraging the overperforming DSOs to keep their current reliability level. Separate baselines are also calculated for underpeforming DSOs, with the aim to reach the average baseline during the regulatory period. One example of this is shown in Figure 2.1. [3, 4]

## 2.2. Denmark

In Denmark, the incentive scheme for ensuring a high reliability of supply is purely based on penalties for insufficient quality of supply, i.e. overachievers are not rewarded.

The models used to benchmark the reliability of supply in Denmark distinguishes between quality of supply on an aggregated level and on a single-customer basis. For the aggregated level, the duration and number of power disruptions for all DSOs are taken into consideration to calculate the target levels for reliability. The target levels of reliability are categorised according to different voltage levels, where specific targets are set for 0.4 kV, 1 to 24 kV and 25 to 99 kV. The number and duration of outages are measured for each DSO, and adjusted relative to the number of customers. The target levels both for number and duration of disruptions in supply, originate in the top 83 percent of the DSOs. For a specific DSO, the line length at various voltage levels are used as input for calculating a weighted target level. This weighting, together with adjustments for the number of customers, ensures that the differences between DSOs are taken into consideration.

A further weighting of disruptions used in the reliability benchmarking is performed according to the type of disruption. The five categories of disruptions include e.g. planned and unplanned disruptions, where different types of disruptions are weighted differently. Unplanned disruptions are weighted highest, as these have the largest societal cost for consumers. The remaining three categories are disruptions due to a third party, force majeure or disruptions due to incidents outside the specific area in question. The two latter categories are weighted with a weight of 0, as these disruptions could not be avoided by the relevant DSO.

Similarly to the Swedish CEMI$_n$ variable, the Danish reliability benchmarking also takes into consideration single customers to ensure high quality of supply for all customers, since the aggregated level only represents average performance. The calculations for the reliability of single customers is similar to the aggregated level, however with the 99.5 percentile rather than the 83 percentile as the reference for the reliability provided. The number of disruptions for customers are categorised into different types, similarly to the aggregated level. [5]

## 2.3. Spain

Spain applies a revenue cap regulation that defines the maximum allowed income per grid company. The reliability aspect enters the regulation in two forms. Firstly a quality bonus (or malus) for security of supply is added to the revenue cap to incentivise efficient and reliable grid operation. Secondly, the starting value for the revenue cap, which should reflect the total incurred cost, is partly defined through a network reference model. The network reference model optimises system costs while accounting for reliability constraints through CENS. The revenue cap is set by:

$$R_t = R_0 \cdot (1 + A_t) + Y_{t-1} + Q_{t-1} + L_{t-1}, \qquad (2.1)$$

where $R_0$ is the starting value which incorporates operating and capital costs. The starting value is based on an the so-called Economic Validation Electrical Reporting Efficient System Tool (EVEREST) which includes a detailed inventory of existing assets, geographical information and a network reference model for performance benchmarking. The starting value $R_0$ is scaled by the rate $A_t$ which accounts for inflation rates in consumer and industrial prices. The factor $Y_{t-1}$ describes additionally allowed revenue due to increased demand and required investments. The remaining two terms represent incentives for the quality of delivered energy. $L_t$ provides an incentive to reduce grid losses compared to a predetermined index. $L_t$ is calculated based on actual grid losses, generated and imported energy and the average electricity price. The factor $Q_t$ incentivises reliability of supply. It is based on indicators that measure the average duration (SAIDI) and frequency of interruptions (SAIFI) which are compared to reference values. To differentiate between different grid areas, each DSO's license area is split into zones according to four categories: Urban, semi-urban, rural concentrated, rural dispersed. The reference values for the duration and frequency of interruptions are set depending on grid areas, the lower the population density the higher the reference level for outages.

In determining the starting value for the revenue cap, the network reference model is used. The model aims at designing an optimal grid system from transmission to distribution. The modelled network is designed to minimise total cost including investment, operation, cost of losses and customer specific CENS. Given the cost constraint, an artificial grid is created based on geographical coordinates of transformers and customers, using a standard cost catalogue for grid assets. [6, 7]

## 2.4. Lessons for the Norwegian benchmarking model

In this chapter we have briefly looked at how the demand for reliability is included in selected international benchmarking models. The treatment of reliability in benchmarking cannot be viewed separately from the other parts of the national regulatory models, and any insights from the international cases must be considered in that perspective. Nevertheless, we can make some observations that are relevant in the Norwegian context. The Swedish and Danish models do not really measure the task of supplying reliability. Instead, they benchmark the performance of the network companies against a reliability metric as a basis for a separate incentive mechanism rather than as an integrated part of the grid companies' performance. The Swedish model does however include customer density to reflect that the task of supplying reliability can differ according to grid structure. This is an aspect that we consider in our analysis as well. The Spanish model includes an artificial grid that takes into account the demand for reliability as well as other factors. This method has some similarities with the methods that we have investigated with respect to the power distance variable.

# 3. Characteristics of the demand for reliability

In this chapter, we describe some of the fundamental economic and technical characteristics of the electricity grid and how the demand for reliability influences grid costs, using a set of stylised example grids. We then present empirical data on outages for the group of network companies to illustrate some of the results from the theoretical analysis. On this basis, we formulate a set of important characteristics that an output variable reflecting the task of delivering reliability should include.

## 3.1. Example grids

Figure 3.1 shows four example grids that illustrate how the task of supplying reliability differs for grid companies with similar demand and distance to customers. Each of the four analysed grids has two connected customers from a substation. The total demand is 200 MW and the distance from the substation to the two customers is 3 km in total.

To compare the illustrated grid system with respect to reliability, we make some further assumptions. Namely:

- The value of reliability is higher for industrial customers than for households, in line with CENS cost functions.
- The probability of an outage increases with line length to a customer.
- Additional factors such as geographical conditions and differences in consumption profiles are disregarded.
- The distance between substation and transformer is the same for all example grids. All other grid infrastructure is the same for all cases.

Before analysing the aspect of reliability, we can make some initial observations based on existing and proposed DEA output variables. All grids have the same number of customers. The total line length in the HVD grid, i.e., in the grid level above the depicted substation, and the number of substations is the same for all grids, given the assumption that the remaining network is the same for all example grids. If the real line length in the LVD grid is accounted for, Grid C and Grid D have 2 km longer lines, due to the reinforcement to the customer with the longer distance from the substation. If a power distance parameter were calculated based on the distance to and power demand of each customer, all grids would be described as having the same task. In this case, power distance would be,

$$P_d = (100\,\text{MW})^{0.4} \cdot 1\,\text{km} + (100\,\text{MW})^{0.4} \cdot 2\,\text{km}. \quad (3.1)$$

Table 3.1 summarises the output parameters for the example grids. Note that the length of HVD lines is not explicitly defined in the test cases but is assumed to be the same for all companies.

**Table 3.1.**: *Overview of output parameters for the four example grids.*

| Grids | A | B | C | D |
|---|---|---|---|---|
| **Number of customers** | 2 | 2 | 2 | 2 |
| **Number of substations** | 1 | 1 | 1 | 1 |
| **Length of lines HVD [km]**[a] | X | X | X | X |
| **Length of lines LVD [km]**[b] | 3 | 3 | 5 | 5 |
| **Power distance [MW$^{\alpha}$km]** | 38 | 38 | 38 | 38 |

[a] Assumed to be the same
[b] Not part of DEA

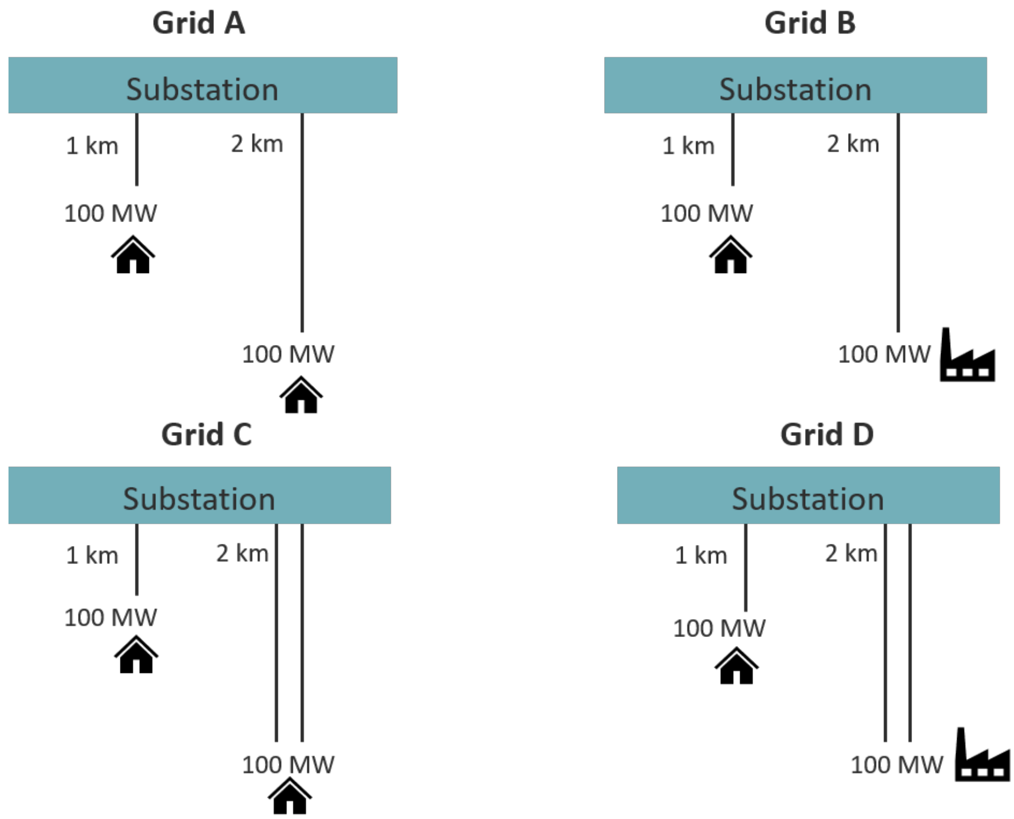



**Figure 3.1.:** *Exemplary grids to illustrate the task related to supplying reliability.*

The overview of existing and proposed output parameters for the DEA model, in Table 3.1, highlights that the task of all four grid companies is described to be the same. This applies both to the existing metrics of number of customers, number of substations and length of HVD lines and to the power distance metric proposed in [8] and [9]. The task of companies A and B compared to grids C and D only differ when the length of LVD lines is considered, which is not currently included in the DEA. When analysing the dimension of reliability for the example grids, however, the associated task and costs vary.

These examples highlight some of the shortcomings of the current benchmarking model. For instance, Grid A will be deemed as more efficient than Grid B. A and B have the same operating and capital costs, while the CENS costs will be higher in B for any outage probability greater than zero. At the same time, the demand for reliability and thus the underlying task of supplying the customers is greater in B.

We can also consider the difference between A and D. D will have greater operating and capital costs. However, the CENS costs will also be lower (assuming that N-1 supply of industrial consumers eliminates outages at this particular node in the grid). While the lower CENS costs will have a positive impact on B's efficiency, the higher operating and capital costs will reduce its efficiency. Again, the outputs in the model are the same, thus leading to B's measured efficiency being lower than the true efficiency.

Another example is the relationship between C and D. These grids are similar in all aspects and will have the same efficiency score in the current benchmarking model. With a correct model D would be more efficient than D.

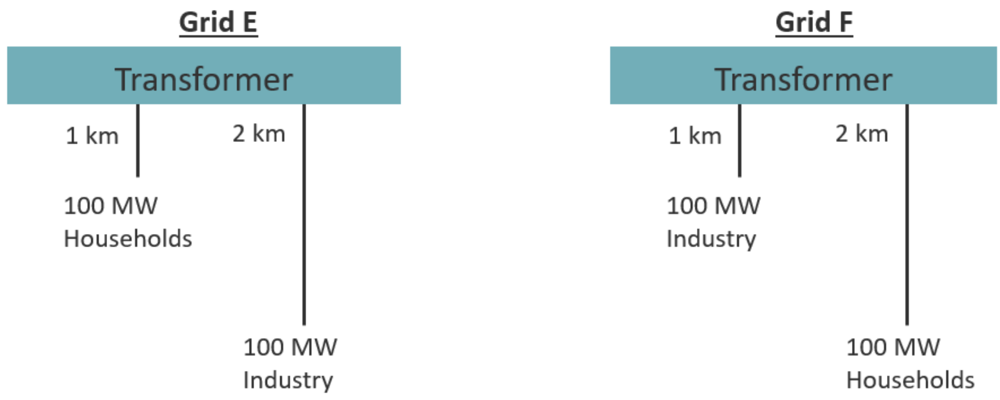



**Figure 3.2.:** *Additional exemplary grids to illustrate the task related to supplying reliability.*

The above example grids can also be used to discuss the economies of scale with respect to supplying reliability. In grid B and D an extra line has been built to the node farthest from the transformer. Assuming that the lines to this node have the same capacity, the cost of supplying extra reliability is likely to be around twice the cost of a single line. However, this applies only to the lines themselves, so the overall cost increase is less than the proportional increase in line costs. Of course, it may also be an option to build an extra transformer as well. In the event that extra capacity is built into the lines (and transformers) to reduce the risk of overloading the grid components, there are obvious economies of scale similar to what we have used in the analysis of power distance. Choosing to build e.g. a line with higher capacity adds little to the overall costs, but the capacity increase will typically be substantial.

We can also have economies of scale related to operational costs, such as keeping stocks of extra grid components to shorten repair times and having manpower available for contingencies and repairs. In general, however, we do not know the relationship between the demand for reliability and the cost of supplying reliability.

Finally, we consider the role of distance on the CENS costs and the task of supplying reliability. We can use the example grids, Grid E and F, in Figure 3.2 to illustrate this point.

Clearly, these two grids are identical in the current benchmarking model and will also have the same power distance. In grid E, the expected CENS costs are higher in the second node located 2 km from the transformer. The longer distance means that outages are more likely to affect the second node. This applies to grid F as well, but here the consumers at the second node farthest from the transformer are households. Hence grid E will tend to have a lower efficiency score than F. However, the higher expected CENS costs in E are a consequence of the industrial customer being located farthest from the transformer and not of any decisions by the grid company. The task of supplying reliability in E is therefore more challenging.

## 3.2. Analysis of actual outage data

To complement the theoretical analysis, we have analysed data on actual outages from the four grid companies, concentrating on the following questions:

- Are certain customer groups more likely to experience an outage?
- Is there a correlation between distance to substation and number of outages?

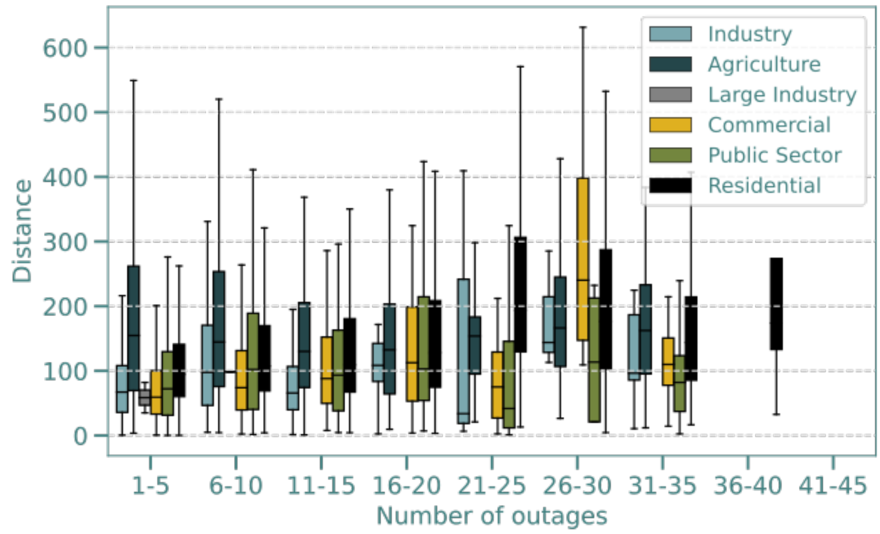



**Figure 3.3.:** *Distance between metering point and connected substation.*

- Are certain areas more exposed to outages? Are outages often occurring in the same geographical area, i.e. at customers linked to the same substation?
- Are outages linked to load profiles? Is an outage more likely to occur in hours of low demand, high demand, high change in demand from the previous hour?

The most interesting finding, although the link is weak, is that customers located the farthest from transformers and substations seem to experience more outages than customers close to the transformers and substations.The distribution of distances to connected substation and closest substation versus number of outages are shown in Figure 3.3 and Figure 3.4, respectively. Also, it seems that there is no link between the overall load in the grid and the risk of outages. On the other questions it is difficult to conclude, as we see no clear pattern.

The results should in any case be interpreted with caution, as they are based on a small sample of Norwegian grid companies and on data for a limited period. The actual outages will also depend on how the grid companies have reacted to the regulation historically, both the economic incentives and direct regulations such as requirements on voltage quality and obligations to connect and supply end-users. Hence, we make no attempt to draw conclusions about causal relationships or statistical significance.

## 3.3. Criteria for a reliability variable

On this background, we can now formulate a set of criteria that we want the reliability variable to reflect:

- Demand for reliability in different customer groups.
- The probability of an outage, particularly linked to distances in the grid.
- Economies of scale.

In addition, the output variable should be exogenous and easy to compute in practice:

- That the variable is exogenous, means that the network companies should not be able to influence the value of the variable.

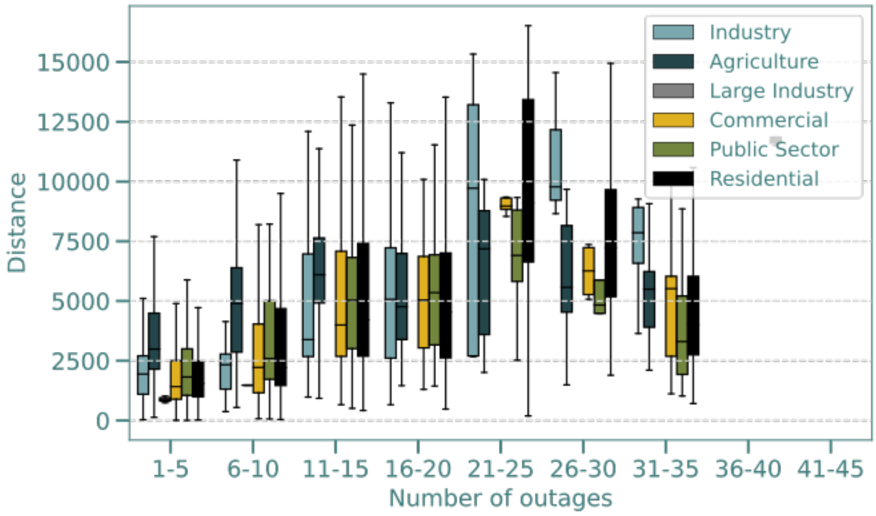



**Figure 3.4.:** *Distance between metering point and closest transformer station.*

- By easy to compute we mean that the variable can be calculated using available data from the network companies without undue processing time.

In the above analysis we have not considered the impact of geographical factors related to e.g. weather and terrain. These factors are handled through the geography correction formula in the current benchmarking model, and we do not make any attempt to include these in the reliability task variables we consider.

# 4. Reliability Measures

In this chapter we discuss how we can define a reliability measure and calculate the measure in practice. Based on the definition of demand for reliability, we introduce and investigate different options to formulate such a metric in the output function of the DEA model. We differentiate between integrated formulations, for which existing or proposed output parameters are weighted to reflect reliability levels, and isolated formulations, where we define separate output parameters that are (partly) independent of the existing output variables. The following list provides an overview of possible metrics.

**Integrated formulation**

1. Reliability weighted number of customers
2. Reliability weighted number of substations
3. Reliability weighted length of lines
4. Reliability weighted power distance

**Isolated formulation**

1. Distance independent demand for reliability
2. Distance weighted demand for reliability
   - geographical distance weighted
   - idealised grid length weighted*
3. Methods using artificial grid architectures

We discuss relevant methods in more detail in the respective sections below and provide initial estimates for the companies in the reference group. The method marked with * will be disregarded in our analysis.

## 4.1. Demand for reliability

A building block of the analysis is an exogenous measure for the customers' willingness to pay for reliability. This measure captures a key part of the task of providing a reliable power supply, namely the demand for reliability from different customer groups. The demand for reliability is independent of the grid companies' decisions and purely a function of the consumption characteristics, e.g. the economic cost of outages for the customers due to lost production, absence of light and heat, loss of data and communication services, damage to equipment etc. For that purpose, we use the CENS functions as a starting point. Over the last decades, CENS has been implemented and refined in the Norwegian income regulation. CENS reflects the socioeconomic cost of an outage, with specific cost functions depending on customer type, time of the outage and power demand. The CENS functions are based on research into the Value of Lost Load (VoLL) for different consumer groups.

To estimate the demand for reliability, we do not use the CENS functions directly. Instead, we define a parameter Value of Energy (VoE). VoE is simply the weighting of power consumption with the corresponding CENS functions per customer group and the relevant adjustment factors for weekday, season, time of day etc. By using this method, consumption in e.g. the commercial sector will have a greater weight than e.g. household consumption. The intuition behind the method is that customers with a high VoLL will also have a high value of the energy that is actually delivered and hence a higher demand for reliable power supply compared to customers with a low VoLL. This higher demand for reliability will in turn increase costs as the grid company will have to take measures to reduce the risk of outages, for instance through N-1 supply (or N-2), higher capacity and keeping spare components and having more manpower available for contingencies.

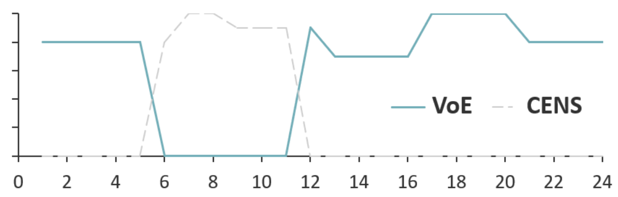



**Figure 4.1.:** *Example of how Value of Energy (VoE) and Cost of Energy not Supplied (CENS) relates to each other during a day with an outage.*

The previous work on implementation and refining of the CENS methodology also provides a framework for evaluating a demand for reliability through the cost functions. The demand for reliability is hence interpreted as the socioeconomic *value* of the actual delivered power, rather than the *cost* of the energy not supplied.

The difference between CENS and the Value of Energy (VoE) is presented schematically in Figure 4.1. In the figure, the CENS is 0 when the power is delivered. When there is an outage, between 06:00 and 11:00, the CENS function varies between hours.

The demand for reliability through the Value of Energy (VoE) is defined as

$$VoE = N \cdot V_{SE} = \sum_{\forall meters} \sum_{t} v(t)_{ref,cg} \cdot f_{m,cg} \cdot f_{d,cg} \cdot f_{h,cg} \cdot \overline{D}_{meter}. \quad (4.1)$$

This is based on the mathematical formulation of the CENS functions, with $N$ customers. The scaling factors for the time of occurrence $f_{t,cg}$ are equivalent to what is used for the CENS functions. The subscripts $m, d, h$ refer to month, day and hour where an outage occurs. In the KILE functions [1] these factors scale the reference cost depending on the time of the outage. The reference cost per customer group $c(t)_{ref,cg}$ is in Equation 4.1 replaced with the value of supplied energy $v(t = 1)_{ref,cg}$. The supplied energy is here considered on hourly basis, although other time resolutions could also be chosen. The choice of time resolution is discussed further in Section 6. The last term considers the average demand $\overline{D}_{meter}$ per metering point. This is based on actual metering data provided by the DSOs involved in this study.

One of the key parameters in Equation 4.1 is the customer group. The difference in value of energy for different customer groups is presented in Table 4.1 for $t \in [1, 10, 60]$ minutes. The numbers presented are equal to what is the case also for CENS. In the table, all customer groups are given the same demand $\overline{D} = 1$ kWh per hour to be able to compare the differences between the customer groups in a standardised manner. By considering the table, it becomes clear that large industry has the highest VoE for both $t = 1$ and $t = 10$ minutes. However, for $t = 60$, commercial customers have the highest value of supplied energy. However, it must also be noted that the numbers presented in Table 4.1 present the value of supplied energy assuming that the demand for different customer groups is equal. This is a simplification, since the different customer groups have characteristic load profiles not represented in the table.

**Table 4.1.:** *Value of energy for different customer groups. Scaled to category max.*

| Customer group | $t = 1$ min [%] | $t = 10$ min [%] | $t = 60$ min [%] |
|---|---|---|---|
| Industry | 28 | 37 | 47 |
| Agriculture | 9 | 13 | 18 |
| Large industry | 100 | 100 | 54 |
| Commercial | 31 | 55 | 100 |
| Public sector | 48 | 60 | 68 |
| Residential | 12 | 15 | 16 |

Another of the important parameters going into Equation 4.1 is the duration for which energy is supplied. In addition to the customer group, Table 4.1 also presents the relative value of energy for different durations $t$. In the CENS methodology, there are six different functions for the outage cost for all customer groups except for residential customers. For residential customers, there are seven functions depending on the duration of the outage $t$. These function are supposed to describe the outage costs for an outage duration $t$ ranging between $t < 1$ minute up to several hours.

Naturally, the choice of $t$ influences the value of the energy calculation. One example taken from Table 4.1 is the cost function for large industry and commercial customers. The large industry customer group has a high electric power consumption, and has a very high cost of short outages. The outage cost for large industry is the highest of all customer groups for both 1 minute outage and 10 minute outage. For an outage of 1 minute, the outage cost of commercial customers is only 30 % of outage cost for large industry customers per kW, However, as the outage duration increases, the relative outage cost decreases. Table 4.1 shows that for an outage of $t = 60$ minutes the large industry customers no longer has the highest outage cost per kW, in fact it is now only 54 % of the outage cost of commercial customers. Thus, the chosen $t$ to be used in Equation 4.1 shifts the task of the DSOs: at a per-hour supplied energy calculation, each commercial customer is worth approximately twice as much as a large industry customer per kW for example. It must, however, be noted that the functions are specified on a per-kW basis, and that different customer groups have an average difference in the magnitude of demand, further influencing the VoE result.

The cost scaling factors are equivalent to what is currently used in the CENS methodology. These factors $f_{p,cg}$ are scaling the value functions to consider the change in socioeconomic value over the month, day and hour.

## 4.2. Integrated formulation

In essence, the integrated formulations of demand for reliability can be explained mathematically as the direct product between a DEA variable and a reliability-scaling as

$$RD_{DSO} = w_r \cdot v_{DEA}, \tag{4.2}$$

where the DEA variable is defined as $v_{DEA}$ and the reliability-weighting is given as $w_r$.

There are several options for including an integrated demand variable for reliability. Current variables in the DEA model are the number of substations, line length in the high-voltage distribution (HVD) grid and number of customers. Another option of capturing the task of supplying reliable power with an integrated parameter is the power distance parameter. As this parameter is currently in the development phase, it is scaled for comparison [10].

## 4.3. Separate formulation

The main idea of the separate formulation is to introduce a new variable to the DEA model, independent of the parameters currently included in the model. This formulation therefore requires a separate methodology for calculation, rather than just a direct scaling of a given parameter. The main target of this variable is to represent the task of the DSOs in demanding a reliable power source.

We consider three options for a separate formulation describing the demand for reliability:

1. Distance-independent demand for reliability
2. Distance-weighted demand for reliability (reliability distance)
3. Methods using artificial grid architectures

### 4.3.1. Distance-independent demand for reliability

For the distance-independent demand for reliability, the methodology is directly based on CENS and described through Equation 4.1. Where the value of supplied energy is denoted as $V_{SE}$, the distance-independent demand for reliability also considers the total number of customers, and is described as $D_R = N \cdot V_{SE}$. The distance-independent demand for reliability therefore consists of three parts: the value function for supplied energy, cost scaling factors, and the demand. These are described in detail above.

### 4.3.2. Distance-weighted demand for reliability

One of the shortcomings of the distance-independent reliability task variable lies in its name, namely the lack of distance considerations. Therefore, the distance-weighted demand for reliability is investigated as an alternative approach.

The distance-weighted demand for reliability can be approached in several different ways, incorporating distance in alternative ways. However, to incorporate distance in a separate formulation, Prim's algorithm based on demand and distance was used for modelling a grid structure in the HVD grid. The exact implementation of this algorithm is presented in "Methods for calculating power and energy distance" [10]. There are, however, a few changes to the original algorithm as used in the power distance analysis. To also incorporate the demand for reliability in the HVD grid, the demand per metering point was adjusted according to customer type. The algorithm will build a line to the node that connects the most reliability-scaled demand with the least amount of km of line.

In this way, Prim's algorithm models a grid construction process, where the reliability-scaled demand is used as input.

### 4.3.3. Methods using artificial grid architectures

A final option could be to construct synthetic or artificial grids that reflect the task of supplying reliability given the type of customer, power use per hour and location in the grid. We would then need to develop an algorithm that builds an optimal grid given the input parameters. In order to use such a method for measuring the task of supplying reliability, we need to make several assumptions about underlying cost functions and measures to increase reliability such as extra capacity, extra grid components etc. This is obviously a very challenging task, and has some similarities with the Swedish benchmarking model from the early 2000's (the Network Performance Assessment Model) that proved impossible to use in practice.

On this basis we do not consider it possible to use this method for representing the reliability task, and exclude it from further analysis.

# 5. Results

In this chapter we describe the results from the quantitative analysis of the options described in the previous chapter. We start by showing our calculation of the demand for reliability, which serves as a basis for all the variables that we analyse in later sections. We then move on to the integrated variables before presenting the results from the analysis of the separate variables.

## 5.1. Demand for reliability

The demand for reliability was calculated for all DSOs as described by Equation 4.1. By summing over all hours and all metering points, the demand for reliability was calculated for the entire system for one year. The resulting value of supplied energy, which is here interpreted as the demand for reliability, therefore ranks the DSOs according to Equation 4.1. In other words, the task of supplying different customers relative to their demand and socioeconomic cost is reflected in the result. Further, to obtain the value of supplied energy $V_{SE}$ as a weighting parameter for the integrated methods outlined in Section 4, the parameter was scaled to the number of customers for each DSO. The demand for reliability with this methodology is presented in Figure 5.1.

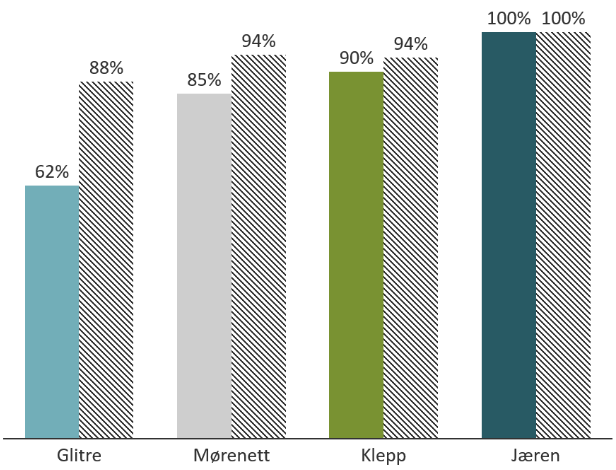



**Figure 5.1.:** *Demand for reliability - value of supplied energy divided by number of customers. Solid bars represent mean demand, diagonally shaded bars represent maximum demand per metering point.*

As the value of supplied energy $V_{SE}$ presented in Figure 5.1 is scaled by the number of customers for each DSO, the smaller grid company, Jæren, can also have the largest value of supplied energy. As outlined in Section 4, the value of supplied energy is a result of both the amount of supplied energy in kWh, the time that energy was delivered, and to which customer group the energy was supplied. Therefore, what is presented in Figure 5.1 is the value of supplied energy for an "average" customer throughout the year. Therefore, as the metric is supposed to represent the task of the DSO, one can also explain Figure 5.1 in that Jæren has the most difficult task in terms of reliability. The customer group composition, as presented in Figure 1.2a sheds some light on this topic. By considering Figures 5.1 and 1.2a together, we observe that there is a negative correlation between the fraction of residential customers and the $V_{SE}$. In other words, when the fraction of residential customers goes down, the value of supplied energy goes up. This is a special case of the four DSOs in this study and cannot be regarded as a general observation since the distribution for other customer types also influences the result. Nevertheless, it demonstrates an interesting trend since the residential customers is the dominating customer group and according to the CENS functions presented Table 4.1, the residential customers have a low value of supplied energy than the other customer groups.

### 5.1.1. Maximum versus average meter demand

When calculating the value of energy we can use different measures, e.g. average demand over a period of time or the maximum demand. The choice of demand (average, maximum or other) in Equation 4.1 affects the resulting demand for reliability to a large extent, as shown in Figure 5.1. In the figure, the demand for reliability is calculated for the four DSOs in this study, we consider either maximum or average demand per metering point through the year.

The solid-coloured bars shown in the figure represent the average power demand per metering point, whereas the diagonally shaded bars represent the maximum demand per metering point. The difference between these two metrics are most apparent for Glitre. Here, the average demand results in a 62 % demand for reliability per customer compared to Jæren. The difference between these two DSOs are therefore 38 %. The origin for this result is discussed above.

Switching perspective from average to maximum demand, the differences between the DSO decrease. The ranking is now also slightly changed, where Mørenett now has a slightly higher value than Klepp. Maybe the most apparent difference, however, is the relative increase for Glitre. The difference between Glitre and Jæren is now reduced from 38 % to 12 %. This large difference has an intuitive explanation in that a few of Glitre's metered customers have a high demand in a limited number of hours. These peak hours are therefore not well represented in the average values for this metering point, but are naturally included and more prominent when the maximum demand is used.

## 5.2. Integrated parameter

The integrated parameters are calculated as presented in Equation 4.2. In the following results for each DSO, the weight $w_r$ is based on the weights presented in Figure 5.1 for average demand.

Resulting values for an integrated parameter for reliability is presented in Figure 5.2. Here, solid-coloured bars denote the current DEA variables, whereas the diagonally shaded area represents the reliability-weighted variables.

First of all, it must be emphasized that the results presented in Figure 5.2 are provided to give an impression of the intuitive application and interpretation of the reliability variables. When, e.g., the number of customers are scaled according to the demand for reliability, the resulting number of customers is reduced for all DSOs other than the largest one. The maximum value in this case, representing the most difficult task of supplying reliable power per customer, is Jæren. This fact is also seen in Figure 5.2, where for Jæren the DEA variables are equal to the reliability-weighted variables. This is exemplified with number of customers, where the effective number of customers for Jæren is 8914 in the current DEA model. With a reliability-weighting of the number of customers, the number of customers for Jæren is still 8914. For Glitre on the other hand, the absolute number of customers is roughly 94 000. However, with a reliability scaling of the number of customers relative to Jæren as a maximum, the effective number of customers for Glitre is closer to 59 000, which means that the number of customers was scaled according to Equation 4.2 with $w_r = 0.62$.

Due to the linear weighting, the resulting integrated parameters shown in Figure 5.2 are only affected by the initial differences between the DSOs. In other words, the relative differences in the current DEA parameters is what changes the outcome for the different variations, since the same weighting is applied for all parameters. Choosing the current DEA variable when including the demand for reliability does therefore not change the underlying assumptions or interpretations of the parameter.

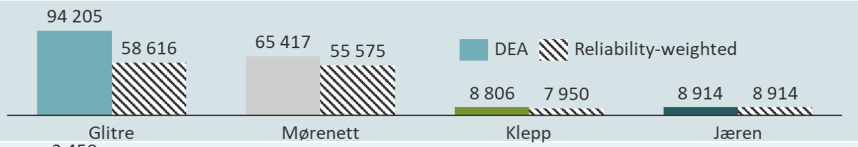
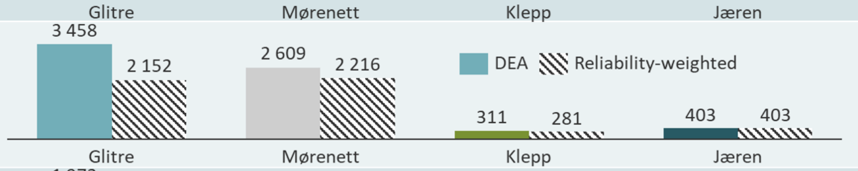
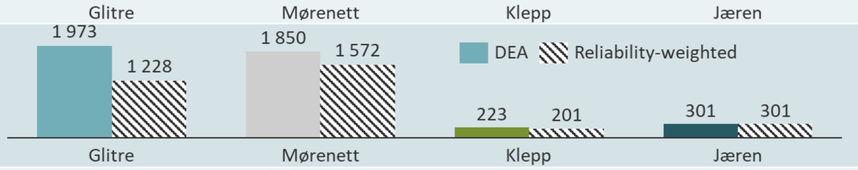
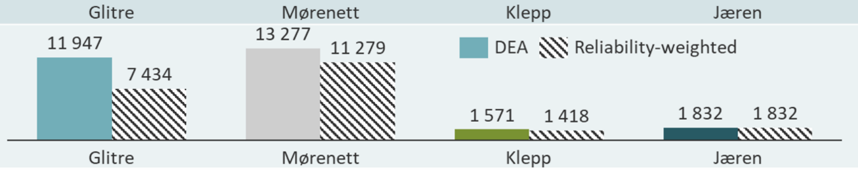
| Method | Results |
|---|---|
| Reliability-weighted number of customers |   |
| Reliability-weighted number of substations |   |
| Reliability-weighted line length |   |
| Reliability-weighted power distance<br>Prim distance – mean demand |   |

**Figure 5.2.:** *Overview of integrated reliability variable compared to the current DEA parameters.*

## 5.3. Separate parameter

### 5.3.1. Distance-independent demand for reliability

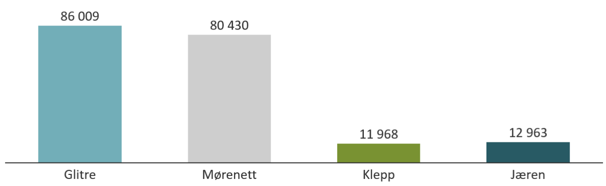



**Figure 5.3.:** *Distance-independent demand for reliability*

The distance-independent demand for reliability is, as explained in Section 4, directly based on Equation 4.1, although without scaling the value of supplied energy to the number of customers. The results presented in Figure 5.3 is therefore equivalent to the absolute value of the solid-coloured bars in Figure 4.1 multiplied with the number of customers. Many of the same observations can therefore be made in this subsection as was done above.

In addition, Figure 5.3 also incorporates the size dimension (number of customers). Since the distance-independent demand for reliability also takes into account the total demand of all metering points in the system, grouped by customer type, the task to supply reliable power to the entire system is considered in this case. Therefore, the intuitive explanation of why Glitre has the most difficult task with this metric is that it is the largest DSO in this study. Further, and maybe of more interest, is the similarity in size to Mørenett. Although Mørenett has fewer customers, it is still considered to have the easier task with this metric, although the absolute differences are smaller than with the current DEA parameters.

Further, looking at the two smaller DSOs, Klepp and Jæren, Klepp is according to this metric considered to have the easier task. The magnitude of the power demand is scaled based on the customer type, representing the task as only supplying reliable power to any customer. The relative importance of the different customers is based on customer type, energy consumption per customer and time of the demand.

### 5.3.2. Distance-dependent demand for reliability (reliability distance)

With a desire to capture also the location of a customer with high demand for reliability in a separate parameter, we have also considered the distance-dependent demand for reliability. The distance-dependent parameter uses Prim's algorithm to approximate the flow length of reliable power in a specific grid area. The method for constructing a grid with Prim's algorithm is explained in THEMA (2021) [10], where it is referred to as Prim demand. The algorithm connects nodes one by one based on the smallest edge cost, which is defined as $L_{edge}/P_{node}^{\alpha}$. Where $L_{edge}$ is the length from an unconnected node to the connected grid system. Using the framework of Prim's algorithm for calculating a power distance, this parameter will further be denoted reliability distance.

The distance-dependent demand for reliability for the four involved DSOs is shown in Figure 5.4. For comparison, the power distance parameter is shown as diagonally shaded bars in the figure.

First of all, we note that the reliability distance metric yields a smaller value for all DSOs. This is a result of the demand scaling as described in point 3 in Section 4. Therefore, since the demand is scaled based on customer type with a value between 0 and 1, the resulting reliability distance yields a lower value than the power distance. This is however not of great importance as the reliability distance would be used as a freestanding parameter in the DEA model, representing the relative task of the DSOs regardless of the absolute values of the parameter. Second, we observe in Figure 5.4 that the relative ranking of the DSOs remain unchanged between power distance and reliability distance. This is, however, not a given. Even though the locations of both metering points, substations and transformers are similar for both parameters, the objectives for the optimisation of Prim's algorithm changes. For the reliability distance, the objective remains the same, namely to minimise the increase in edge cost for each node as described in THEMA (2020) [10]. However, for the reliability distance,

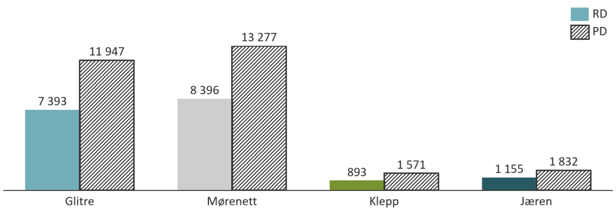



**Figure 5.4.:** *Distance-dependent demand for reliability (RD) compared to the power distance (PD).*

the reliability-weighted demand is used as input for the edge cost. By considering Figure 5.4, the general trends appear to be similar for both parameters. However, due to the limited sample number of DSOs, it can not be concluded that this trend will persist for a larger number of DSOs.

Third, the relative difference between the power distance and reliability-distance is worth considering. As the reliability-weighted demand is used as input for Prim's algorithm, the difference between the original demand and the reliability-scaled demand reveals that most of the observed effect is due to the demand effect rather than a distance effect. The changes in the demand metric is smallest for Mørenett among the four DSOs. On the other side of the scale is Klepp, having the largest reduction in demand due to the reliability weighting. For Klepp, the reliability-weighting scales the demand to about 30 % of the original demand. This is explained both by the customer groups making up the demand base for Klepp, the demand distribution for these customer groups, and by their respective load profiles. These characteristics also partly explain why Klepp has the lowest fraction $RD/PD$ in Table 5.1: namely due to the highest reduction in demand. These results contrast the results presented above, i.e. in Figure 5.1, where Klepp is ranked higher. In other words, when the demand for reliability is matched to where the demand source is located, the task of Klepp is defined as easier, while when location is not taken into account, Klepp's task is considered more difficult relative to the other DSOs.

The second parameter making up the reliability distance is the line length in the HVD grid. Prim's algorithm will in this case consider the edge cost of the reliability-weighted demand together with the line length while constructing the grid. Therefore, as the relative difference between the weight of metering points with varying customer groups changes, the line lengths increase slightly. The cost of constructing a slightly longer line is then compensated by a larger difference in demand between two substations. The difference between the four represented DSOs were observed to be small in this study, with line lengths increasing between 2 to 3.5 % from the line length with Prim's distance considering distance and original demand.

**Table 5.1.:** *Distance-dependent demand for reliability compared to power distance.*

| Method | Glitre | Mørenett | Klepp | Jæren |
|---|---|---|---|---|
| $RD$ | 7393 | 8396 | 893 | 1155 |
| $PD$ | 11947 | 13277 | 1571 | 1832 |
| $RD/PD$ | 62 % | 63 % | 57 % | 63 % |

# 6. Evaluation

In the previous chapter, we analysed several different options for including reliability in the DEA benchmarking model. In this section we evaluate the options according to the criteria we have set out: the probability of outages, economies of scale, exogeneity, and computational ease. We also discuss some of the remaining challenges to be solved.

## 6.1. Assessment of options against the evaluation criteria

All the variables reflect the demand for reliability in the same manner, as they are all based on the CENS functions per customer group. With respect to other criteria, they are markedly different. We discuss these differences below.

### 6.1.1. Probability of outages

In the theoretical analysis we argued that line lengths and distance from transformers and substations are major factors affecting the probability of outages. The reliability-weighed number of customers and distance-independent demand for reliability only reflect the reliability demand of the customers and do not take into account line lengths. While the reliability-weighted line length directly incorporates the overall length of lines per grid area, it does not take into account the distances between transformers and substations. The reliability-weighted number of substations can also be said to capture some of the probability of outages as the number of network components is also a factor influencing the probability. The more components, the higher the expected number of failures for a given underlying probability of failure per component. However, we consider that this is a secondary factor compared to geographical distance and hence not a major advantage of this particular variable. It is also an endogenous parameter that the grid companies can influence. On the other hand, the two methods that are based on the power distance algorithm include the distance between transformers and substations, which reflects the probability of outages.

### 6.1.2. Economies of scale

In the power distance calculation we included the scaling parameter alpha to reflect economies of scale. In principle it is possible to include a scaling parameter in all of the variables we have investigated. In the reliability-weighted power distance and distance-weighted demand for reliability we include the scaling parameter alpha. It is however not obvious that the scaling parameter alpha should be the same for the distance-weighted demand for reliability.

In the power distance calculation alpha is included to reflect the economies of scale. For the same line capacity, it is cheaper to use one strong line than two weaker ones. This is accounted for by the alpha parameter in the power distance element. This link is less clear with respect to the demand for reliability. However, we do not have any evidence to suggest what the related scaling parameter should be. In the variables that do not include the distance and the related scaling parameter it is instead possible to scale the demand for reliability. For instance, if the value of reliability per unit (e.g. kW) is 100 for the customer group with the highest value and 10 for the group with the lowest value, the scaled weight for the group with the highest value could be set to 5 instead of 10 (100/10) to reflect economies of scale. It is however difficult to estimate the right value of this scaling parameter.

### 6.1.3. Exogeneity

The variables based on substations and line lengths are clearly linked to factors that the network companies can influence, and have similar characteristics with respect to exogeneity as the current DEA variables. The variables based on power distance or the reliability distance are not fully exogenous but are less endogenous than the variables based on substations and line lengths. The exogeneity of the power distance parameter itself is discussed in (THEMA, 2021) [10]. The distance-independent demand for reliability only reflects customer characteristics and is fully exogenous, assuming that the grid companies are not able to manipulate the customer group data (we assume that these opportunities are limited due to the existing systems for registration of customer group and historical data available to RME). The same applies to the reliability-weighted number of customers.

### 6.1.4. Computational ease

We consider that all of the variables are possible to calculate in practice and that the necessary data will be available. For the reliability-weighted power distance and the distance-weighted demand for reliability this assumes that the power distance is included as a variable in the benchmarking model either alone or as an integrated variable weighted with reliability. These two options are nevertheless

**Table 6.1.:** *Options for a separate demand for reliability.*

| Method | Demand for reliability | Probability of outages | Economies of scale | Exogeneity | Computational ease |
|---|---|---|---|---|---|
| Reliability-weighted number of customers | Yes | No | No, unless weighting is non-linear | High | High |
| Reliability-weighted number of substations | Yes | Number of components | No, unless weighting is non-linear | Low | High |
| Reliability-weighted line length | Yes | Line lengths | No, unless weighting is non-linear | Low | High |
| Reliability-weighted power-distance | Yes | Through line lengths and number of substations and transformers | Yes, through $\alpha$ parameter | Medium | Medium |
| Distance-independent demand for reliability | Yes | No | No, unless weighting is non-linear | High | High |
| Distance-weighted demand for reliability | Yes | Yes, through line lengths and number of substations and transformers | Yes, through $\alpha$ parameter | Medium | Medium |

more complex than the other options, which merely require the first step of the calculation where demand is differentiated according to the reliability weights of the customer groups.

## 6.2. Conclusion

In this chapter we have evaluated the options for including the demand for reliability in the DEA benchmarking model according to a set of criteria. We conclude that the distance-weighted demand for reliability is the most suitable option. This variable reflects both the demand for reliability and the probability of outages and is to a large extent exogenous. It is also not too complicated to compute. It can also be tailored to reflect economies of scale with respect to the supply of reliability. Including a separate variable for reliability can reduce the incentive power of the benchmarking model as more output variables lead to a higher proportion of the network companies being judged as efficient. This is however an assessment that RME must make based on their views of the full model, including the geographical corrections.

# 7. Recommendations and conclusions

We have investigated different options for including the task of supplying reliability in the DEA benchmarking model for the distribution grid. Our analysis is based on a sample of only four network companies and there are remaining questions that need to be resolved before a method can be more firmly recommended. However, based on the analysis, we can provide some recommendations on how RME can move forward and how the remaining questions can be analysed.

## 7.1. Recommendation on choice of output variable for reflecting reliability.

We conclude that the task of supplying reliability is better represented by being included as a separate variable rather than being included in an existing variable. From the perspective of efficient benchmarking as few variables as possible is desirable, as fewer grid companies will be on the efficient frontier with fewer outputs in the model. However, this must be weighed against other criteria, notably exogeneity and economies of scale. We find that the integrated variables where we weigh existing or proposed variables with the demand for reliability fail to capture one or more these aspects adequately. Furthermore, the weighting through multiplication of a reliability measure with the variable in question can seem arbitrary. Hence, we recommend that RME considers either the distance-independent or the distance-weighted demand for reliability for inclusion in the DEA model. In order to choose between the two options and design the parameter appropriately, some key issues need to be investigated further.

## 7.2. Remaining research questions

**Baseline for calculating the demand for reliability.** In the analysis we have used the CENS functions for each customer group to calculate the value of reliability for the grid companies. The CENS functions constitute the best available knowledge on the value of reliability for the grid customers and is therefore a key factor in describing the task of supplying reliability. However, there are still issues that need to be considered before defining an output variable based on the CENS functions. We have used the CENS cost for outages of 1 hour as a basis. From a network planning perspective, we believe that 1 hour or longer durations is a useful point of reference. For longer durations the results are fairly similar to the 1 hour estimates, while shorter durations can give significantly different rankings of customer groups, and by extension of grid companies. A way forward could be to collect information about network planning practices and assumptions about outage duration, to see how these feed into decisions about investments and other measures in the grid. This should give further insight into the task of supplying reliability and how it can be measured.

**Should distance be included in the reliability variable?** The key factor for choosing between the distance-independent or the distance-weighted demand for reliability is the impact of distances in the grid on the task of supplying reliability. As we have argued, there are good theoretical reasons for believing that there is a significant impact of distance, which means that the distance-weighted demand is the better choice all else being equal. We have also shown that it is possible to calculate such a variable using the data and algorithms from our work on power distance. Our analysis of outage data also indicates that there is such a link in practice. Also, to the extent that there is such a link, it may be explained by the location of different customer groups and the grid companies' optimal adjustment to CENS costs. The dataset is limited to four companies and represents a short period of time. Therefore, we cannot draw any conclusions about whether there is a statistically significant link between distance and the probability of outages, and, by implication, the task of supplying reliability. To investigate the need for including distance in the reliability variable further, more data from a larger set of grid companies will be useful. A more detailed analysis of the location of different customer groups can be a part of such an extended analysis. One can also collect qualitative information from interviews with grid companies about their planning practices and the role of distances in the task of supplying reliability to gain a better understanding. In this context, RME should also consider the role of the geography correction in the second stage of the current DEA setup. Conceivably, the effects of distance can be highly correlated with the impact of geographical framework conditions. In theory, a correctly designed reliability variable that includes distance should then also have an effect on the impact of geography on efficiency. Conversely, a distance-independent reliability variable can still be viable provided that the geography correction also reflects the distance element. This should be looked at in more detail.

**Analyse economies of scale with respect to reliability.** We have argued that there are economies of scale in supplying reliability. This is linked to the underlying technical and economic characteristics of electricity networks. However, there are reasons to believe that the economies of scale with respect to reliability differ from those of supplying power. Essentially, dimensioning a line or other grid components with extra capacity to supply extra power is cheap given that the component is going to be built anyway. While this is an aspect of the economies of scale for reliability as well, given that extra capacity can reduce the risk of overloading components, the building of extra assets to achieve e.g. N-1 supply is a more important measure to increase reliability. We suspect that the implicit economies of scale are significantly smaller for N-1 measures than for adding extra capacity to an asset under construction. Another factor is the need for stocks of reserve parts and manpower to handle faults in the grid, where again we would expect economies of scale but perhaps not to the same degree as building extra capacity. To analyse this further, one approach could be to analyse actual technical and cost data from grid companies to see how they have built their grids to ensure the desired level of reliability. One could also use these inputs to construct simple (but still fairly realistic) synthetic grids to see how the overall costs change with different levels of the demand for reliability. This would then enable RME to get more knowledge about the economies of scale with respect to reliability, which is relevant for both of the options we recommend to consider for inclusion (distance-independent vs. distance-related) in the DEA model.

# A. Acronyms

**CEMI$_n$** Customers Experiencing Multiple Disruptions

**CENS** Cost of Energy Not Supplied

**DEA** Data Envelopment Analysis

**DSO** Distribution System Operator

**HVD** high-voltage distribution

**NRA** National Regulatory Authority

**NVE** Norges Vassdrags- og Energidirektorat

**RME** Reguleringsmyndigheten for Energi

**SAIDI** System average interruption duration index

**SAIFI** System average interruption frequency index

**VoE** Value of Energy

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**THEMA Consulting Group**

Øvre Vollgate 6
0158 Oslo, Norway

support@thema.no
https://www.thema.no/

**Berlin office**

Friedrichstrasse 68
10117 Berlin, Germany

NVE
Reguleringsmyndigheten for energi – RME


Reguleringsmyndigheten for energi

MIDDELTHUNS GATE 29
POSTBOKS 5091 MAJORSTUEN
0301 OSLO
TELEFON: (+47) 22 95 95 95



www.reguleringsmyndigheten.no