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Does Weather Explain the Cost and Quality Performance? An Analysis of UK Electricity Distribution Companies

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Abstract

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Keywords Data Envelopment Analysis, electricity, weather, quality of service.

JEL Classification L15, L51, L94JEL

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1. Introduction

It is commonly believed that the cost and quality of service performance of electricity distribution network operators (DNOs) can be affected by various non-discretionary and environmental factors. In particular, climatic conditions are often regarded as important determinants of the performance of network utilities. The rising adoption of incentive regulation and benchmarking of distribution utilities requires ample attention to the role and treatment of such non-controllable factors.

Several studies have shown that weather conditions influence the quality of service in electricity distribution networks. For example, Coelho (2003) and Domijan (2003) find a significant correlation between weather parameters such as rain, wind, and temperatures and power interruptions. The latter study shows that the impact of higher temperatures on transformer failure interruptions is more significant than that of lower temperatures. Billington and Allan (1984) show that in adverse weather conditions, the failure rate of a component can be considerably higher than in normal conditions. Wang et al. (2002) show that the restoration time during winter storms is considerably longer than during normal weather.

At the same time, it can be argued that, over time, utilities adapt their operating and investment practices to the adverse effects of their environment and the effect of these need not be significant. It is therefore difficult to formulate hypotheses with respect to the effect of weather conditions on the performance of networks. Also, there is insufficient empirical evidence on the extent to which climatic conditions affect the quality performance of network utilities and how these should be accounted for in the context of incentive regulation and the benchmarking of utilities.

The effect of weather on the cost and quality performance of U.K. utilities has not previously been studied. This paper presents an empirical approach to examine the relationship between weather conditions and the efficiency of network utilities in terms of operating and capital costs as well as their quality of service. The results of the study will help improve the modeling of efficiency analysis and regulatory benchmarking of utilities. We use factor analysis (FA) to compress a set of related weather variables into two composite variables. We also apply the data envelopment analysis technique (DEA) to calculate the efficiency of a progressively comprehensive set of models. We then use second stage DEA analysis to examine the effect of composite as well as individual weather parameters on the efficiency of the utilities.

Section 2 provides an overview of quality regulation and benchmarking of electricity distribution in the U.K. Section 3 reviews the relationship between climatic conditions and quality of service. Section 4 presents the Factor Analysis (FA) and multi-stage DEA as well as the procedures used in data collection. Section 5 describes the data and models used in the study. Section 6 summarizes the results. Section 7 presents the conclusions.

2. Benchmarking Quality of Service in the U.K. Distribution Networks

Electricity distribution utilities in the U.K. are subject to efficiency improvement requirements in proportion to their potential for reduction in operating costs. Ofgem has applied the corrected ordinary least squares (COLS) technique for benchmarking of the DNOs' operating expenditures since the second five-year price control review effective from 1995/96. Their regression model comprised normalised operating costs of the DNOs as the dependent variable and a composite output variable as the independent variable comprising customer numbers, network length, and units of energy delivered. The (COLS) method was also used for the fourth price control review effective from 2005/06 without any general glide path beyond the start of the next control period (Ofgem, 2004). A detailed description of the background to the reform, incentive regulation and benchmarking, and the performance of the DNOs is given in Jamasb and Pollitt (2007).

As cost is the only dimension measured in the current system of regulatory benchmarking, there is concern over whether cost saving may be achieved at the expense of service quality. In order to regulate the quality performance, the U.K. regulator, Ofgem relies on a separate mechanism under the Information and Incentive Project (IIP). Two important quality indices are used: the number of customers interrupted per 100 customers (CI) and customer minutes lost per connected customer (CML). Between 2001 and 2003, average CI fell from 83.1 to 75.3 and average customer minutes lost (CML) from 79.7 to 71.1 minutes (Ofgem, 2004b). An analysis of data between 1991/92 and 2003/04, showed a correlation coefficient of 0.86 between CI and CML.[1] However, in individual cases, improvement in CI does not necessarily result in lower CML. Ofgem assigns a higher incentive percentage for DNOs to achieve CML than CI targets, indicating the relative importance of reducing the length as opposed to the number of interruptions. Thus, in this study we focus on the number of customer minutes lost.

[1] The data for 1990/91 is excluded due to the occurrence of some exceptionally high CML figures.

Although Ofgem has adopted the COLS technique in regulatory benchmarking, DEA has been used for crosschecking purposes (Ofgem, 2004c). Giannakis, et al. (2005) introduce a benchmarking model using DEA, which considers the inclusion of quality of service. Benchmark rankings of relative performance change significantly when quality attributes are introduced. Yu, et al. (2007) expand the model by including distribution losses. Using the input prices, partly obtained from a willingness-to-pay (WTP) survey, they find relatively low allocative efficiency indicating a mismatch in allocating resources among expenditures, service quality, and network energy losses. The results suggest that the utilities may not be correctly incentivised to achieve socially optimal trade-offs between these.

Ofgem recognizes that variations in quality of service performance among DNOs can be due to inherited differences, inherent differences, incurred differences and exceptional events (Ofgem, 2006). The inherited factors refer to network design and configuration. The inherent differences include topographic factors such as network length and customer density, while incurred factors refer to managerial decisions in relation to operating and maintaining the network.

In calculating Customer interruptions (CI) and Customer minutes lost (CML), Ofgem, and the Quality of Supply Working Group, have considered the inherited and inherent differences and excluded exceptional events. With this method, physically similar parts of networks are investigated and performance is compared at a disaggregated level. The DNO’s CML and CI are adjusted for events that are beyond their control, caused by a third-party, act of God or exceptional incidents such as transmission or other connected network faults; third party damage such as vandalism or terrorism; damage from birds and animals that could not reasonably have been prevented; and other events including restricted access due to foot and mouth disease control restrictions. For transmission or other connected network faults, 10% of the duration of interruptions is included in assessing performance against quality targets. Although such interruptions are beyond DNOs’ control, they can take action to mitigate their duration. If an interruption is caused by the failure of protection equipment or fire resulting from failure of a DNO’s own equipment, no adjustment is made (Ofgem, 2004b). DNOs can appeal for adjustments to their quality performance indicators (CML and CI) for exceptional events and, if confirmed, the full impact is disregarded. For one-off exceptional events, only CI and/or CML exceeding the relevant thresholds are excluded.[2] The size of the adjustment is determined by whether the DNO has taken reasonable steps to prevent the incident and restore power in an efficient and effective manner.

[2] CI and CML thresholds are shown in Table 4.9 in Ofgem (2004, p.24).

Although Ofgem considers and exempts severe or exceptional events, normal weather conditions are not used for the purpose of quality assessment. In other countries such as Norway weather conditions are used to calculate the expected level of energy not supplied (ENS) for each distribution firm and hence the expected level of interruption costs. ENS is the amount of energy that would have been supplied to the customers if the interruption had not occurred. Interruption costs are calculated for each firm annually based on the estimation of ENS and average specific interruption costs for each customer category (Langset, 2002).

3. Environmental Factors

3.1 Climatic conditions and power interruptions

Some studies have previously examined the effect of environmental and climate factors on the performance of electric utilities. A study of quality of service in Norway based on interruption statistics and voltage quality measurement attributes the main causes for energy not supplied (ENS) as follows: 40% being related to environmental factors, 20% to technical failure, and 5% as human-related. Unknown or non-specific factors account for a further 32% and 1% respectively. The results also show that the number and duration of interruptions are significantly higher in overhead networks compared to cable networks (Kjølle et al., 2003). Domijan et al. (2005) use the Poisson regression model to test the significance between normal weather conditions and frequency of power outages in 16 regions of Florida Power and Light distribution system between 1998 and 2001. Normal weather conditions, which refer to the daily variables such as rainfall (inches), wind (daily two-minute maximum speed in miles/hour) and average dew point (average temperature), are considered. The study reveals that the effect of dew is less significant than rainfall and that wind is the most significant factor affecting the total number of daily outages.

Other studies focus more specifically on weather impact on overhead distribution lines. Zhou et al. (2006) use Poisson regression and Bayesian network methods to model the failure rates of these lines. Weather data such as daily speed of wind gusts, icing (ice pellets and freezing rain), and days of lightning spanning from 1998 to 2003 in and around Manhattan and Kansas are used. The results reveal the presence of different probabilistic relationships between each weather condition and the level of network failure.

Korhonen et al.(2003) use two weather conditions and one quality dimension in DEA models. The sample consists of 106 DNOs in Finland and the most comprehensive data is from the year 1998. Forest cover (km^2) in the distribution area is used as a proxy for increased construction costs and risk of interruption. Average snow depth in the winter (cm) is used as a proxy for conditions related to winter conditions. A three-year average of customers' total interruption time (hour) is used as a quality indicator and is treated as a non-discretionary input. Linear regression is applied to examine the joint effects of the variables. The effect of weather variables is tested by adding or removing them from the DEA models according to the changes in the average efficiency scores. Based on these tests, variables for snow and forest cover are excluded. It is still possible, however, that the weight of these variables on the individual efficiency of some firms could be very high.

3.1.1 Normal weather conditions

Although there is no clear classification of weather conditions, parameters such as temperature, rain, wind and humidity are generally categorized as normal; and hurricanes, storms and tornadoes as extreme. Lightning is sometimes considered in the latter category. Weather conditions such as gale and hail are also considered in some studies (Domijan et al., 2003; Zhou et al., 2006). However, temperature-related conditions such as concrete temperature, airfrost and groundfrost, which also affect the performance of distribution systems, have not been used. In this study, we consider the most common weather conditions faced by DNOs and classify these into two categories: Main temperature variables (min. temp, airfrost, groundfrost, concrete temp); and other weather conditions (total rainfall, hail, thunder, max. temp and gale). The term severe weather conditions used by Ofgem normally refers to different degrees of storm severity and is not considered in this paper.

3.1.2 Temperatures

Most of the existing literature examines the relationship between seasonal climate factors and electricity demand. The main focus is on modeling the forecast daily electricity loads. Simple meteorological and derived variables such as temperature, wind speed, heating and cooling degree-days are often used (Prado et al., 2002; Sailor et al., 1997). Maximum and minimum temperatures are the preferred measures of thermal climatic indices for analyzing the electricity demand peaks or troughs (Valor et al., 2001). Temperature in general is considered to be inversely correlated with electricity consumption as demand tends to surge with decreasing temperatures (winter) due to the use of electric heating appliances and increasing temperatures (summer) as a result of using cooling appliances (Hor et al., 2005).

The Intergovernmental Panel on Climate Change (IPCC) reports that global average surface temperature is projected to rise by 1.4-5.8°C by 2100, relative to 1990 (IPCC, 2000). Based on a baseline projection, an estimated climate change-induced temperature of 1 to 1.4°C in 2010 will lead to an increase of 3 to 6% in peak demand and 1 to 2% in consumption. In addition, an increase of 3.5 to 6.5% in combined annual costs and cumulative capital costs is projected (Franco et al., 2008). Traditionally, summer months with lower network demand provide a buffer period for DNOs to schedule outages for maintenance purposes (KEMA, 2007).

Other than maximum temperature, concrete temperature, airfrost and groundfrost provide a standard measurement of ‘minimum’ weather elements by taking the surrounding environment into account. Concrete temperature is less subject to local weather influences than ground frost. Concrete temperature is related to urban island effect (UIE) as the climate of an urban observation station differs greatly from those of the surrounding countryside (MET, 2008). Given the nature of concrete, which absorbs heat during the day, and that city surfaces are unable to radiate heat away as fast as those in rural areas, temperatures fall more slowly in urban than rural areas at night. These temperatures provide a good account of the climatic differences between DNOs in urban and rural areas.

3.1.3 Hail, gale and lightning

Hail, gale and lightning are considered to be the most influential weather phenomena on the reliability of power systems (Brown, 2002). Hail refers to solid precipitation in the form of balls or pieces of ice (hailstones) with diameters ranging from 5 to 50 mm or more (MET, 2008). Hail can cause damage only when individual stones reach around 15 mm in diameter. Chunks of ice stones falling from cumulonimbus clouds in conjunction with wind gusts can bring down distribution lines.

In general, the density of lightning strikes to lines on a stormy day correlates to the frequency of outages (Zhou et al., 2006). In the U.S., for example, 30% of power outages are lightning-related and have cost utilities over US$100 billion annually in damaged and destroyed equipment (EPRI, 2006). Although pylons are constructed to mitigate this risk as much as possible, electrical components are vulnerable to the larger peak current amplitudes of lightning flashovers.

A gale (Force No. 8) is defined as a wind speed of greater than 34 knots over any 10-minute period; it is capable of breaking twigs off trees and generally impeding progress (MET, 2008). The scale as provided by the Meteorological Office, ranges from Force 0 (Calm), 1 (Light air) to 11 (Violent Storm) and 12 (Hurricane force). There is a potential combined movement of vegetation and conductors caused by routine winds, which causes voltage sag. In some cases, the wind-gust speeds exceed the design strength of the distribution structures. For example, in the case of the supply interruption following Boxing Day in 1998 in the U.K., the mean wind speeds were nearly 60mph, with gust of over 90mph and even over 100mph recorded in some areas.

3.1.4 Rainfall

Compared to other weather parameters, rainfall is more location specific. Combined with high winds, heavy rainfall can damage overhead distribution systems. Primary systems such as feeders, laterals and oil circuit breakers are highly sensitive to the impact of wind and rain. The failure of non-primary systems including transformers caused by weather conditions is the primary cause of power outage (Coelho et al., 2003). Taking the above-mentioned interruption in 1998 as an example, stations recorded rainfall of between 400mm and 800mm in the West, and 200mm to 300mm in the East in one day. These levels of rainfall combined with the minimal evaporation typical during the winter, were thought to be sufficient to cause the soil to soften, which in turn increased the likelihood of trees being uprooted by the strong winds (Offer, 1999).

Some studies have shown how individual weather conditions such as air temperature and lightning affect the performance of power plants. Furthermore, other variables such as wind speed might be correcting terms for the influence of temperature (Engle et al., 1992; Li et al., 1995). Hackney (2002) highlights the increasing importance of combined weather variables for utilities' decisions with respect to their operating environment, which contain more information than single-variable reporting. The present paper is the first study of its kind, at least in the context of the U.K., where the aggregate effect of weather parameters is used to evaluate the performance of DNOs.

3.2 Managerial Decisions and Power Interruptions

Environmental factors such as weather conditions are obviously beyond the management control of utilities. However, there is also a possibility that utilities located in areas with poorer climate conditions perform better in efficiency measurement than those with more favorable weather. Managerial decisions including vegetation management, undergrounding, asset investment and maintenance can contribute to mitigation of weather impacts. All of these factors can affect capital spending and operating cost or quality of service.

3.2.1 Vegetation management

Power outages can be classified into weather-related failures and tree-caused failures. Both types of failures are random and therefore difficult to prevent completely (Zhou et al., 2006). Distribution wires are lower voltage and close to the ground and are threatened by weather primarily through falling or breaking trees. Furthermore, sprouting tree branches can come into contact with energized conductors, causing failures.

In order to improve network resilience, previous studies suggest vegetation management is the first priority to improve operational practices (Ofgem, 2004b). Tree-cutting costs can be a good expedient to reduce operating expenditure in order to meet the requirements of efficiency improvement laid down by Ofgem. According to Prospect, a trade union organization comprising engineers and other professionals, there is some evidence that cost allowances in the U.K. for exceptional events had not been spent by firms in the previous price control reviews (Prospect, 2004). The fourth Distribution Price Control Review (2005/06-2009/10) includes specific allowances totaling £70 million per year for vegetation management (tree-cutting), exceptional events and quality improvements (increased allowance for fault costs) (Ofgem, 2004b). Since Ofgem forecasts an increase in tree-trimming requirement above 2002/03 levels, additional operating cost allowances are set to cover the direct cost of vegetation management (Ofgem, 2004b).

In order to ensure that tree-trimming programs are in place to improve performance during severe storms, the Electricity Safety, Quality and Continuity Regulations 2002 were amended in October 2006 (DTI, 2006). Under this amendment, U.K. distribution firms are responsible for certain vegetation management standards, which come into force on 31 January 2009. Firms are required to maintain sufficient clearance between their overhead lines and trees and other vegetation so as to prevent electrical or physical contact between them causing interference or interruption.

3.2.2 Overhead lines and underground cables

Overhead lines are more vulnerable to damage in adverse weather than underground cables. Maintenance, including regular line inspection and subsequent remedial actions, becomes important. The operating and maintenance costs of overhead lines are higher compared to that of undergrounding. On the contrary, undergrounding has higher capital costs. The trade-off between quality of supply and network costs also varies from rural to urban areas. Areas such as Manchester, with a higher degree of urbanization, are likely to have better quality of service due to more meshed and underground networks compared to those with more rural areas such as the islands and highlands of Scotland. The costs of operating and maintaining networks in forested and mountainous areas are likely to be higher due to the difficulty in gaining access to these areas (CEPA, 2003). Table 1 shows the percentage and length (km) of overhead lines and underground cablesfor each UK DNO. There is a significant difference in the percentage of underground cables between DNOs.

Table 1: Percentage of overhead lines and underground cables for UK DNOs

	CN East	UU	CE NEDL	CE YEDL	WPD S Wales	WPD S West	EDFE SPN	EDFE EPN	SP Dist	SP Manweb	SSE Hydro	SSE Southern
	Circuit length km (2003/2004)											
Overhead lines	**23,303**	**13,710**	**15,118**	**13,852**	**18,242**	**28,555**	**12,890**	**34,744**	**21,246**	**21,457**	**31,186**	**27,743**
% of total	34%	23%	38%	27%	54%	59%	26%	38%	35%	45%	70%	37%
Underground cables*	**45,719**	**41,656**	**22,490**	**37,510**	**15,502**	**16,915**	**37,047**	**57,424**	**38,581**	**26,681**	**12,888**	**42,124**
% of total	66%	71%	56%	73%	46%	35%	74%	62%	64%	55%	29%	56%
Total	**69,035**	**58,701**	**40,118**	**51,362**	**33,744**	**48,378**	**49,948**	**92,168**	**59,886**	**48,147**	**44,437**	**75,491**

* Excluding submarine cables and CONSAC underground cables at LV (Source: Ofgem (2004), Quality of service report, Excel Data 2004/05)

3.2.3 Asset investment and maintenance

A continuing challenge for DNOs is how to improve the resistance of infrastructure to adverse weather whilst keeping costs low. Hardening distribution lines, which includes upgraded poles, smaller conductors, shorter spans, push braces and less pole-mounted equipment means increasing capital expenditure. From investments in system components such as covered overhead conductor systems to advanced equipment, including lightning detection networks capable of providing accurate cloud-to-ground lightning stroke data there is a need for management support. Other than upgrading systems, distribution firms require sufficient revenue in order to replace ageing infrastructure, maintain the network adequately, and invest in improved quality of service (House of Commons, 2004).

With good risk management, distribution firms should recognize the heightened risk of equipment failure during periods of adverse weather (House of Commons, 2003). DNOs can minimize the risk of equipment failure through appropriate network planning, equipment design, maintenance and operation. From a prevention perspective, strengthening infrastructure to cope with exceptional weather conditions such as gale and hail becomes fundamentally important. From a remedy perspective, faster restoration also comes with a high price tag. Using mobile generation and hot glove/live line techniques can restore supply and fix faults more quickly. This involves additional cost such as investment in LV and HV fault-finding equipment in order to locate the faults more accurately.

House of Commons (2004) points out that in several major incidents, power outages are caused either directly or in a contributory way by maintenance problems. The continuous pressure to reduce expenditure on staff costs is criticized as the main reason for the shortage of permanent skilled staff. Technically competent workers with local knowledge, who contribute to rapid restoration during interruptions, are critical to efficient maintenance work (Prospect, 2004).

4. Methodology

4.1 Data Envelopment Analysis

In recent years, DEA has been popular with regulators as an analytical tool in incentive regulation of network utilities (Jamasb et al., 2001). The technique was first presented in Farrell (1957) as a measure of firm efficiency using multiple inputs and outputs. DEA is a non-stochastic technique that uses linear programming and optimization to obtain the efficiency and best-practice frontier from a sample of firms. The efficient frontier envelops the less efficient firms whose distance from the frontier is interpreted as a measure of inefficiency. A relative efficiency score between zero and one is calculated for each firm from the ratio of the sum of weighted outputs to the sum of corresponding weighted inputs.

DEA models can be specified as constant returns to scale (CRS) or variable returns to scale (VRS). CRS models, used in this study, assume that efficiency is not affected by the size of firms. As the UK DNOs are all large, there is no compelling reason to focus on the effect of scale in this study. DEA models can also be specified as input or output oriented. Since the distribution utilities are required to provide services to all customers in their territories, the level of outputs and services is beyond their control. Thus, we use an input-oriented DEA model, assuming a fixed level of output and strong disposability in both inputs and outputs. The disposability assumption implies that an increase in inputs does not result in a reduction in outputs; or that less output can be produced with the same amount of inputs.

The computation of the technical efficiency score for the *i*th firm in a sample of N firms in a CRS model is shown in Equation 1. θ is a scalar and λ is a I x 1 vector of constants. X and Y denote N x I input and M x I output matrices respectively assuming N observed inputs and M observed outputs. In VRS models, a convexity constraint $\Sigma\lambda=1$ is added which ensures that the firm is compared against other firms of a similar size.

Cost minimization - Technical efficiency (TE)

$$
\begin{aligned}
& Min_{\theta,\lambda}\theta \\
& \\
& subject\ \ to \\
& -y_i + Y\lambda \geq 0, \\
& \theta x_i - X\lambda \geq 0, \\
& \lambda \geq 0
\end{aligned}
\qquad [1]
$$

If the value of θ — i.e. the technical efficiency (TE) score for the *i*th firm is equal to 1 - it means that the input levels cannot be reduced proportionally. This indicates a point on the frontier and hence a technically efficient firm (Farrell, 1957). If min θ is smaller than 1, the firm is dominated by the frontier. Equation 1 is solved *N* times to obtain a value of θ for each firm. In order to obtain allocative efficiency (AE) scores, another set of linear programs are required to measure economic efficiency (Equation 2) where w_i is a vector of input prices for firm *i* and x_i^* (calculated by the LP) is the cost-minimising vector of input quantities for the i-th firm, given the input prices w_i and output levels y_i (Coelli et al., 2005). The total economic efficiency of firm *i* is calculated from EE = $w_i' x_i^* / w_i' x_i$. The allocative efficiency scores are then calculated residually by EE = AE * TE (Coelli et al., 2005).

Cost minimization – Allocative efficiency (AE)

$$
\begin{aligned}
& Min_{\lambda, xi*} w_i' x_i^* \\
& \\
& subject\ \ to \\
& -y_i + Y\lambda \geq 0 \\
& x_i^* - X\lambda \geq 0 \\
& \lambda \geq 0
\end{aligned}
\qquad [2]
$$

It should be noted that the allocative efficiency computed by our DEA models differs from conventional allocative efficiency analysis where the quantity and price of all financial input factors are specified individually. In our models, allocative inefficiency indicates that a firm is either not subject to the correct price of quality and/or that the DNO uses the wrong bundle of inputs.

4.2 Two-stage DEA

Two-stage DEA allows for the effect of non-discretionary variables such as weather parameters to be examined. In the first stage, we calculate the relative technical and economic efficiencies in selected models using traditional inputs and outputs. Technical efficiency measures a firm's ability to minimize inputs to produce a given level of outputs. Using the input quality (customer minutes lost) and respective factor price (WTP to avoid one minute of interruption), we measure the allocative efficiency of the utilities – i.e. the component of economic efficiency attributable to choosing the right mix between cost and quality inputs. In this study, we are concerned with the technical efficiency (TE) and economic efficiency (EE) of different models.

In the second stage, we examine the effect of weather composite variables obtained from Factor Analysis as well as individual weather parameters on the efficiency of the utilities using Tobit regression analysis. Tobit regression is a censored regression model, which estimates the relationship between an explanatory variable and a truncated or censored dependent variable. DEA scores range from 0 to 1 but X_1 and X_2 can take values from negative to positive infinity. The latent variable Y* is unobserved for Y and is generated by the classical linear regression model as characterized in Equation 3, where X_1 and X_2 are weather composite variables (Weather index I and II) and β_1 and β_2 are regression coefficients. The error term μ is assumed to be normally distributed i.e. $\mu \sim N(0, \sigma^2)$.

$$
\begin{aligned}
&Y^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \mu \\
&Y = Y^* \quad \text{for} \quad Y^* > 0 \qquad\qquad [3] \\
&Y = 0 \quad \text{for} \quad Y^* \leq 0
\end{aligned}
$$

The estimated regression coefficients can be used to adjust the efficiency scores for the effect of non-discretionary factors (e.g. average weather conditions). The advantage of this method is that we do not need prior assumptions regarding the direction of the influence of the categorical variables. A weakness of two-stage method is that it only considers radial inefficiency and ignores the slacks. Also, if the variables used in the first stage are highly correlated with the second-stage variables, the results are likely to be biased. However, two-stage DEA is a practical method often used for examining the effect of environmental variable (see Yang et al., 2008 and Nillesen et al., 2008).

4.3 Factor analysis

Compressing a large number of related weather variables into composite variables offers a practical solution for modeling efficiency with DEA. Factor analysis (FA) is a multivariate statistical method widely used in the social sciences to extract composite factors from a set of observed variables. There are several extraction techniques such as confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). In this study we use the EFA method as we have no prior knowledge that the intended factors are measured by the observed variables. The number of factors extracted is determined by examining Eigenvalues from the analysis. In CFA, the researchers must specify the number of factors to be measured *a priori*.

Another variable reduction technique is principal component analysis (PCA). There is no consensus among statistical theorists as to what conditions should determine the use of FA or PCA. Some statistical scholars prefer factor analysis to components analysis (Bentler et al., 1990; Gorsuch, 1990; Widaman, 1990). Some argue that the difference between the two is negligible or that PCA is preferred (Arrindell et al., 1985; Steiger, 1990; Velicer et al., 1990). For example, Velicer et al. (1990) discover a high degree of similarity between the results from both methods. Therefore, neither method is likely to produce any empirical or substantive differences.

PCA assumes that all variance is common variance and is shared by other variables included in the model. The total variance in the common factor model is partitioned into common variance and unique variance. Factor analysis considers unique variance, which is specific to a particular variable and includes an error component representing random measurement error. We consider weather parameters as the only indicators of the latent constructs to be measured. As the error (unique) variance might represent a significant portion of the total variance, FA has the advantage of considering error due to unreliability in measurement. On the contrary, PCA assumes absence of outliers in the data. Moreover, FA is more appropriate when links between the observed variables and their underlying factors are unknown or uncertain. We therefore choose the FA technique to arrive at a comprehensive effect of weather variables on network performance. We expect the interpretable constructs obtained from FA can maximally explain the covariances among a set of weather variables.

We use exploratory factor analysis to extract the factors after testing the correlation of the weather parameters. We retain factors that have Eigenvalues larger than unity (Table 2). Eigenvalues indicate the proportion of variance explained by each factor. As a result, we retain two factors (Factor 1 and 2) that cumulatively explain 92 % (61% and 31%) of the total variance of the data. After estimating the factor loadings (the correlation between observed variables and factors) through extraction, we use varimax (orthogonal) rotation to impose a restriction on the correlations between two factors. The aim of rotation is to simplify and clarify the data structure by maximizing high loadings and minimizing low loadings. This in turn facilitates the interpretation of results. We then compute the Bartlett scoring which gives the individual factor scores. Factor scores are estimates of underlying latent constructs and are obtained from the multiplication of factor loading (correlation coefficient) and raw data (annual weather data). The corresponding coefficient of each weather parameter for each factor is shown in Table 3.

Table 2: Results of exploratory factor analysis

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	3.74223	1.83086	0.6127	0.6127
2	1.91137	1.3884	0.3129	0.9256
3	0.52297	0.1179	0.0856	1.0112

Table 3: Results of Bartlett factor scoring

Weather Parameters	Scoring Coefficient Weather Index I	Scoring Coefficient Weather Index II
MaxTemp (Cº)	-0.06084	-0.36931
MinTemp (Cº)	-0.23231	0.04946
Total Rainfall (mm per day)	-0.02221	0.31908
Hail (day)	-0.06023	0.29321
Thunder (day)	-0.09362	-0.32463
Airfrost (day)	0.25111	0.02056
Groundfrost (day)	0.25615	0.05486
ConcreteTemp (day)	0.25399	0.04261
Gale (day)	-0.08021	0.30176

Based on weather parameter data from 1995/96 to 2002/03, we construct two weather indices (Weather index I and II) using the score coefficients of each weather parameter in each year. Minimum temperature, airfrost, groundfrost and concrete temperature carry higher loadings in Weather index I (Factor 1) whereas in Weather index II (Factor 2), maximum temperature, thunder, hail and gale have the higher weightings (Table 3). Thus a pattern emerges where the main temperature variables (Index I) and other weather characteristics (Index II) are represented by two distinct indices (Factors 1 and 2). These indices will be used as the non-discretionary variables in the second stage of the DEA.[3]

5. Data and Model Specifications

5.1 Choice of variables

Customer numbers (CN) and units of energy delivered (EDF) are the most commonly used outputs in benchmarking of distribution network utilities. We use these outputs given that the pricing of distribution services varies according to both of these. There is a lesser consensus on using network length (NL) as an output though it has been used as an output by Ofgem.

We use customer minutes lost (CML) as a quality attribute of output; a reduction in which is regarded as desirable. In order to include CML in a DEA model, we multiply the values by the number of customers, to make the variable scalable. In this study, energy losses (EL) are treated as an input that is to be minimized. We include monetary values of Opex and Totex in our model as inputs. Totex is the sum of Opex and non-operational capital expenditure.

All yearly weather data is used in order to make maximum use of the information available for each DNO. Other than temperatures, which are expressed in degrees Celsius, and rainfall in mm, the remaining parameters are as per day values.

5.2 Data

We compare the performance of 12 DNOs in the U.K. for the 1995/06 to 2002/03 period. The monetary and physical data for the inputs and outputs are based on publications and information from Ofgem. To capture the weather pattern year to year and ensure continuity, we need to maintain the consistency of the source of cost data. Thus, we have dropped 2003-04 data from the analysis, which had been subject to adjustment in order to control for weather related atypical costs. The data on service quality is mainly based on information from Ofgem's annual Electricity Distribution Quality of Service Report. We use

[3] The Factor Analysis was conducted using STATA.

input prices in order to measure economic efficiency (EE). The unit price of CML is the value of willingness-to-pay (WTP) for avoidance of a one minute power interruption (domestic plus business).[4] The WTP data is derived from the Ofgem-Accent's customer survey of WTP for quality of service in 2004 (Ofgem, 2004a). The details of the method used for calculation of WTP for domestic and business consumers are described in Yu et al. (2007). Energy loss (EL) is measured in GWh and valued at average industrial electricity price. The price of Opex and Totex is by convention set to 1.

The weather data were obtained from the UK Meteorological office for most observation stations. Complete data records of weather in the service areas of two utilities EDF-LPN and CN-West were not available. The MORECS[5] map divides the UK territory into 190 40-km^2 areas, enabling the location of MET observation stations to be traced to service area (Appendix I). The accuracy of the location coverage is further verified by the post codes of each DNO area and observation stations. Two weather stations in the service area of the DNOs were selected to represent each firm. The average of the two stations was taken. In some cases, where weather data for two observation stations were not available, we use data from one station. The data for maximum and minimum temperatures during the year are chosen. The total yearly rainfall in mm and total number of days of the remaining weather parameters are used. Table 4 shows the definition of the weather parameters.

Table 4: Definition of weather parameters

Weather Conditions (I)	**Descriptions**
Min. Temp.	Minimum air temperature (degrees C).
Air Frost	Number of days when minimum air temperature was below zero degrees C.
Ground Frost	Number of days when minimum grass temperature was below zero degrees C.
Concrete Temp	Number of days when minimum concrete temperature was below zero degrees C.
Weather Conditions (II)	
Total Rainfall	Total rainfall (mm).
Hail	Number of days when hail fell (00-24 GMT) ie. solid precipitation (of which outer parts are clear ice) with a diameter 5mm or more.
Thunder	Number of days when thunder was heard (00-24 GMT).
Max. Temp.	Maximum air temperature (degrees C).
Gale	Number of days when mean wind speed over any 10 minute period reached 34 knots or more (Force 8) (00-24 GMT).

[4] We use CML * no. of customers as quality of service input. Hence we use WTP / no. of customers as input price.

[5] MORECS: Met Office Rainfall and Evaporation Calculation System. It is the generic name for MET services involving the routine calculation of soil moisture and evaporation for Great Britain.

Table 5 shows the yearly average for each weather parameter. The DNOs in Scotland have the lowest temperatures on average over the 8-year period than those in other areas. The service area of SP Distribution has the highest level of total rainfall: almost double that of CE-YEDL, which has the lowest figure. More than half of the DNOs have experienced less than 10 days of thunder on average over the period.

Table 5: Yearly average of weather parameters (1995 – 2002)

DNOs	Max. Temp.	Min. Temp.	Ttl Rainfall	Hail	Thunder	Air Frost	Ground Frost	Concrete Temp	Gale
Yearly Avg	*Degree C*	*Degree C*	*mm*	*Days*	*Days*	*Days*	*Days*	*Days*	*Days*
EDF - EPN	23.04	0.31	672.52	1.64	19.36	47.75	88.66	61.72	3.14
CN East	22.03	1.16	685.51	0.99	16.55	36.06	87.27	68.84	1.67
SP Manweb	20.52	1.48	771.36	0.74	7.55	38.12	86.94	46.52	14.02
CE - NEDL	19.99	-0.43	812.25	1.77	8.45	53.70	105.57	72.99	2.92
UU	21.00	0.78	1191.57	3.88	15.13	35.38	75.25	50.25	0.75
EDF - SPN	22.67	1.72	759.22	2.19	17.77	27.49	72.47	45.44	2.79
SSE-Southern	22.89	0.63	868.80	0.57	10.88	49.23	98.84	65.55	2.01
WPD S Wales	19.86	2.47	1006.57	8.06	7.58	19.69	55.06	38.45	25.34
WPD S West	19.95	3.53	1052.31	0.65	8.65	11.41	55.41	31.68	9.29
CE - YEDL	20.71	1.45	641.57	0.46	5.45	20.90	63.37	35.78	8.10
SSE - Hydro	17.53	-0.11	997.24	3.68	4.05	53.02	117.80	81.15	16.72
SP Distribution	18.94	-0.28	1236.04	2.40	5.44	63.74	125.32	94.68	3.88

5.3 Model specifications

We use a set of progressively more comprehensive DEA models. We specify two types of DEA models – i.e. cost-only and cost-quality-loss models. Cost-quality-loss models are generally preferable to the cost-only model that is currently used by the regulator (Yu et al., 2007). In addition, technical and economic efficiency are calculated for single factor models as well as for more comprehensive models.

Table 6 summarizes the cost inputs, input prices, outputs, and quality of service attributes used in the models. The technical efficiency and economic efficiency scores of these models are then tested against the two weather composite indices and individual weather parameters using Tobit regression in the second stage DEA.

Table 6: Model specifications – Input/output

Model	1	2	3	4	5	6
Inputs						
OPEX	√	√		√		
TOTEX			√		√	√
CML		√	√	√	√	√
EL		√	√	√	√	√
Input price						
1 (TOTEX)				√	√	√
WTP (CML)				√	√	√
ENGY PRICE (LOSS)				√	√	√
Output						
CN	√	√	√	√	√	√
ED (EDF)	√	√	√	√	√	√
NL	√	√	√	√	√	
Tobit regression (second stage)	**TE**	**TE**	**TE**	**EE**	**EE**	**EE**
Weather Index I	√	√	√	√	√	√
Weather Index II	√	√	√	√	√	√

OPEX: Operating expenditure TOTEX: Total expenditure EE: Economic efficiency
CML: Duration of interruptions EL: Energy physical loss WTP: Willingness-to-pay
ENGY PRICE: Energy Price CN: Total number of customers NL: Total network length
ED: Energy delivered TE: Technical efficiency

Model 1: Model Opex

Model Opex is the base model and resembles Ofgem's COLS model. Ofgem treats Opex as input while number of customers; energy delivered; and network length are treated as components of the composite size variable (output). Technical efficiency (TE) is measured in Models 1-3 and economic efficiency is measured in Models 4-6.

Model 2: Model Opex-CML-Loss

Model 2 (Opex-CML-Loss) extends Ofgem's base model to incorporate important quality dimensions such as customer minutes lost and energy losses. The model outputs remain the same.

Model 3: Model Totex-CML-Loss

The total Cost-CML-Loss model, incorporating service quality by including customer minutes lost and energy losses, is preferable to a Opex cost-only model. Model Totex-CML-Loss is the most comprehensive approach and was used in Yu et al. (2007).

Model 4: Model Opex-CML-Loss

Model 4 is similar to Model 2 but economic efficiency is measured.

Model 5: Model Totex-CML-Loss

Model 5 is similar to Model 3 but economic efficiency is measured. Customer minutes lost and energy loss are considered as the inputs that focus on quality of service. The outputs are number of customers, energy delivered and network length.

Model 6: Model Totex-CML-Loss (without Network length)

Network length represents the geographical dispersion of distribution firms. Since it might correlate to weather, we drop the network length as an output in this model.

6. Results

6.1 Correlation - Individual weather parameters and composite factors

Correlation coefficients can reveal the relationship between weather factors. Table 7 shows the correlation coefficients for the parameters for the 1995/96 – 2002/03 period. The composite variable weather index I exhibits a low and negative correlation with weather index II. This confirms the usefulness of using two separate composite weather indices in DEA models, representing two rather distinct types of weather conditions.

For individual weather parameters, airfrost shows a high correlation with groundfrost and concrete temperature. A similar high correlation is seen between hail and gale. The high correlations between individual weather parameters reinforce the need to use factor analysis to produce composite variables for weather effect.

Table 7: Correlation - Individual and composite weather parameters

1995-2002	Weather I	Weather II	Max Temp	Min Temp	Ttl Rainfall	Hail	Thunder	Air Frost	Ground Frost	Concrete Temp	Gale
Weather I	1										
Weather II	-0.32	1									
MaxTemp	-0.02	-0.53	1								
MinTemp	-0.89	0.24	-0.07	1							
TtlRainfall	-0.35	1.00	-0.49	0.27	1						
Hail	-0.28	0.41	-0.22	0.16	0.40	1					
Thunder	-0.17	-0.17	0.61	0.13	-0.12	-0.04	1				
AirFrost	0.94	-0.10	-0.11	-0.86	-0.12	-0.14	-0.18	1			
GroundFrost	0.93	0.00	-0.20	-0.82	-0.03	-0.19	-0.25	0.91	1		
Concrete Temp	0.93	-0.01	-0.17	-0.83	-0.04	-0.12	-0.17	0.92	0.94	1	
Gale	-0.36	0.22	-0.42	0.35	0.18	0.51	-0.37	-0.29	-0.30	-0.30	1

6.2 Correlation - weather composite and other DEA variables

We also obtain the correlation coefficients drawing on the raw data for each parameter from 1995/96 – 2002/03. Weather index I shows a positive correlation with the cost and quality parameters while weather index II exhibits the opposite. This is consistent with the above discussed features of the dominant components in each weather index.

As mentioned in the methodology section, one disadvantage of the two-stage DEA approach is that if the variables used in the first stage (Totex, Opex, CML, Losses, Network length) are highly correlated with the second-stage variables (weather composite indices in this case), the results are likely to be biased. As seen in Table 8, both second-stage variables (weather composite indices) show a low correlation with cost, quality and other parameters. Weather composite indices show a low correlation with network length, explaining only 8% of the features (Corr. Coefficient 0.2935). The directions and correlations of this relationship run counter to our expectations, as they do not reflect the conventional wisdom that the longer the network, the more it is likely to be affected by climate.

Table 8: Correlation - Weather composite indices and DEA variables

1995-2002	Weather I	Weather II	Opex	Totex	CML	Losses	Network Length
Weather I	1						
Weather II	-0.3192	1					
Opex	0.177	-0.3105	1				
Totex	0.1499	-0.2222	0.868	1			
CML	0.1273	-0.0774	0.1584	0.2531	1		
Losses	0.2452	-0.1625	0.268	0.4915	0.3939	1	
Network Length	0.2935	-0.1917	0.3434	0.5941	0.5477	0.8038	1

6.3 Correlation between weather composite and network lines

As shown in Table 9, weather index I has a low correlation with the percentage of overhead lines and undergrounding. Weather index II, representing larger weather variability, shows a higher correlation with undergrounding. Following from this and consistent with the nature of each weather index, weather index I shows a positive correlation with the percentage of undergrounding while index II exhibits the opposite. There is a need to further study the relationship between undergrounding of lines, quality of service and expenditures.

Table 9: Correlation - Weather composite and % of overhead lines and undergrounding

1995-2002	Weather I	Weather II	Overhead line (%)	Undergrounding (%)
Weather I	1			
Weather II	-0.3192	1		
Overhead line %	-0.0334	0.2294	1	
Undergrounding %	0.0427	-0.2879	-0.9783	1

6.4 Models 1-6 – Technical and economic efficiency

The average technical and economic efficiency scores for Models 1-6 are summarized in Table 10. The results indicate that DNOs are, on average, technically inefficient by about 30% at the highest (Model 1) and 3% at the lowest (Model 3). This implies that an output level can be maintained while reducing operating expenditure by about 3% and 30% over the period. In DEA, adding or deleting variables or changing the sample size can change the shape of the production frontier and thus the efficiency scores. The mean efficiency in Models 2 and 3 seems to increase with the number of input variables.

For technical efficiency, United Utilities ranks low (No. 8) in the simple model M1 (Opex-only) but ranks high (No. 1) in the comprehensive model M2 (Opex-CML-Loss) after taking quality and energy losses into account (Table 10). This implies a possible trade-off between expenditure, energy losses and service quality.

Table 10: Average technical and economic efficiency scores (Models 1-6)

Model 1995/96-2002/03	M1 Opex Only TE	M2 Opex-CML-Loss TE	M3 Totex-CML-Loss TE	M4 Opex-CML-Loss EE	M5 Totex-CML-Loss EE	M6 Totex-CML-Loss Drop NL EE
EDF – EPN	0.84	0.99	1.00	0.88	0.92	0.90
CN East	0.51	0.93	0.99	0.72	0.79	0.75
SP Manweb	0.63	0.93	0.96	0.88	0.90	0.86
CE – NEDL	0.53	0.92	0.94	0.73	0.81	0.77
UU	0.66	1.00	1.00	0.88	0.87	0.87
EDF – SPN	0.73	0.92	0.95	0.79	0.89	0.89
SSE – Southern	0.92	0.95	0.99	0.91	0.92	0.91
WPD S Wales	0.50	0.87	0.85	0.55	0.58	0.53
WPD S West	0.78	0.98	0.98	0.92	0.93	0.75
CE YEDL	0.69	1.00	1.00	0.98	0.99	0.99
SSE – Hydro	0.87	1.00	1.00	0.91	0.92	0.47
SP Distribution	0.72	0.88	0.95	0.78	0.81	0.70
Sector Average	**0.70**	**0.95**	**0.97**	**0.83**	**0.86**	**0.78**

6.5 Second-stage analysis - Efficiency scores and composite weather variables

In the second-stage analysis, we use Tobit regression to test the effect of composite weather variables (Weather index I and II) in different models. The efficiency scores of each model are regressed against the two composite variables simultaneously. We find no significant weather effect in the single factor model Model Opex (M1), the comprehensive models Model Opex-CML-Loss (M2) and Model Totex-CML-Loss (M3) (i.e. technical efficiency models), or in the economic efficiency model Opex-CML-Loss (M4) (Table 11).

However, we find a significant weather effect in the economic efficiency model Totex-CML-Loss (M5) (Weather Index II only). Also, when we exclude network length from the outputs in Model 6 we find a significant weather effect (Weather index I and II). This implies that network length partially reflects the weather effect.[6] To further verify the effect of network length, we dropped the network length variable from models 1 to 4. The result is consistent with that of the single factor technical efficiency model - Model Opex (M1), i.e. insignificant for Weather Index I and II. In more comprehensive models, however, more weather parameters are significant.

Technical efficiency Models 2 and 3 show significant weather effect (Weather Index I and II). In the economic efficiency Model 4 the weather effect is also significant (Weather Index II only). Thus, in the absence of network length, the weather effects become more evident. This may be because network length per unit of input is higher in DNOs with worse weather and hence the network length output may be a proxy for the weather effect. In testing the relationship between individual weather parameters (e.g. rainfall, gale) and different models using Tobit regression, we find evidence of multi-co linearity of weather parameters in most models.

Table 11: Average efficiency scores and results of Tobit regression by model

Model No.	**Input**	**Output**	**DEA Measure**	**Stage 1** DEA Score Sector Avg	**Stage 2** Tobit Regression	**Weather composite variables**
Model 1	Opex	CN, ED, NL	TE	0.70	not significant	Weather Index I & II
Model 2	Opex-CML-Loss	CN, ED, NL	TE	0.95	not significant	Weather Index I & II
Model 3	Totex-CML-Loss	CN, ED, NL	TE	0.97	not significant	Weather Index I & II
Model 4	Opex-CML-Loss	CN, ED, NL	EE	0.83	not significant	Weather Index I & II
Model 5	Totex-CML-Loss	CN, ED, NL	EE	0.86	Significant	Weather Index II
Model 6	Totex-CML-Loss	CN, ED	EE	0.78	Significant	Weather Index I & II

[6] This may also be due to lower number of variables in the model.

6.6 Second-stage DEA – Adjustment of efficiency scores

Second-stage DEA allows adjustment of efficiency scores relative to a common environment (average weather conditions). Regression coefficients β_1 or β_2 are used to adjust the efficiency score of each DNO. Table 13 shows the adjustment of DEA scores for Model 5, using the corresponding β_2 (Weather Index II). After making adjustments to the efficiency scores, the rankings of 4 DNOs remain the same. The rankings of 4 DNOs improve, and those of 4 DNOs worsen. The degree of change in ranking is, however, small, normally moving up or down one or two positions.

Table 13: Magnitude of weather impact on efficiency scores
M5: Model Totex-CML-Loss, Economic Efficiency

1995-2002	DEA Score	Weather_I	Weather_II	diff. WII	Adjusted Magnitude	Adjusted %	Adjusted DEA Score
EDF – EPN	0.92	31.80	209.71	-74.52	0.04	4.6%	0.96
CN East	0.79	30.32	214.54	-69.69	0.04	5.0%	0.83
SP Manweb	0.90	23.06	248.15	-36.08	0.02	2.3%	0.92
CE – NEDL	0.81	38.78	260.43	-23.80	0.01	1.7%	0.82
UU	0.87	11.29	375.94	91.71	-0.05	-6.0%	0.82
EDF – SPN	0.89	16.35	236.16	-48.08	0.03	3.1%	0.91
SSE – Southern	0.92	32.28	275.26	-8.97	0.01	0.6%	0.92
WPD S Wales	0.58	1.45	326.58	42.35	-0.02	-4.1%	0.56
WPD S West	0.93	-1.90	333.39	49.15	-0.03	-3.0%	0.91
CE YEDL	0.99	13.54	203.37	-80.86	0.05	4.7%	1.00 *
SSE – Hydro	0.92	38.97	327.54	43.31	-0.02	-2.7%	0.89
SP Distribution	0.81	42.65	399.72	115.48	-0.07	-8.1%	0.75
Sector Average	**0.86**	**23.22**	**284.23**			**-0.17%**	**0.86**

W I, WII: Weather index I and II Adjustment Formula: (weather II – avg. weather II) * β_2 β_2 = -0.0005691

* Normally efficiency scores should not be larger than 1. This firm performs particularly well and exhibits super efficiency.

Similar adjustments are also made to Model 6 for which the results are significant (Weather I & II). Table 14 summarizes and compares the magnitude of adjustment for two models. The adjustment ranges from -25.1% to 11.6%. Clearly, controlling for weather effects has a significant impact on economic efficiency in some models.

Table 14: Magnitude of weather impact on efficiency scores - Models 5 and 6

Model	Model 5	Model 6
Average DEA Score	0.86	0.78
DEA Measure	EE	EE
Statistically Significant	Weather II	Weather I & II
Max Adjustment (%)	5.0%	11.6%
Min Adjustment (%)	-8.1%	-25.1%
Avg Adjustment (%)	-0.17%	-1.15%

7. Conclusions

In this paper, we have investigated the effect of weather conditions on the costs and service quality performance of utilities. We find a significant correlation between weather composite variables and the economic efficiency scores of comprehensive models. With regard to technical efficiency, the effect on all models is insignificant. For economic efficiency measurement, Models Totex-CML-Loss (M5) and Totex-CML-Loss (dropping network length) (M6) are significant. Thus, the main temperature variables (Weather index I) and other weather conditions (Weather index II) in our case have an impact on the performance of DNOs but the magnitude of their effects is small on average.

Hence we find some evidence of statistical significance between weather and cost and quality performance. The size of adjustment of efficiency scores in some models based on average weather conditions is noticeable. The rankings of over 60% of DNOs changed after the adjustment. The impact on some DNOs is larger than for others. However, the overall economic significance of these changes is relatively small. On the other hand it may be argued that the weather in Great Britain does not vary enough to make a difference and there are no extremely large or extremely small distribution firms in our sample, which creates insignificant effect for environmental variability.

With the exception of Model Opex (M1), the weather parameter is significant in all models (M2 – M6) after dropping network length. This suggests that including network length as an output in the case of the U.K. internalizes the effect of weather on efficiency scores. This in turn justifies the use of network length as an output in Ofgem's current benchmarking model. In a previous study Yu et al. (2007) show that by taking customers' willing-to-pay for quality into account, a Totex-CML-loss model is preferable to the Opex-only model used by Ofgem. The findings of the present study suggest that more comprehensive technical efficiency models and economic efficiency models with Opex may not need to include weather variables explicitly. On the other hand, more comprehensive models based on Totex may need to incorporate weather effects.

From a management perspective, while severe weather conditions such as storms can test a utility's crisis management and contingency planning abilities, normal weather conditions reflect the capability for daily operation. Although weather conditions are found to be immaterial for efficiency measurement, this should not deter utilities from improving their operating and investment practices to mitigate the adverse effects of their operating environment. These practices include vegetation management, undergrounding and assets investment and maintenance. Although weather variability is beyond the control of utilities, these tools are at the disposal of utilities to mitigate weather-related risk. Furthermore, although DNOs continue to improve their service quality year by year, it becomes difficult to achieve noticeable differences beyond a certain quality standard.

Although the impact of weather on efficiency performance is small on average, DNOs need to recognize the challenges of coping with increasing weather variability and severity due to climate change. From a risk management perspective, climate change-induced temperature increases may further increase the probability of system overload. The electricity network in the U.K. was built largely in the 50's and 60's; and overhead lines were not built to withstand exceptional weather conditions such as storm winds and lightning. Some of these lines are now nearing the end of their useful economic life. Working to reduce the vulnerability of the electrical distribution system to weather-related disturbances should be an area of focus for DNOs.

Apart from providing an empirical basis for climatic impact studies, this research also provides insight into how cost and quality performance in electricity distribution is affected by weather. Based on the results, we can conclude that DNOs in the U.K. are not in a disadvantaged position due to weather conditions. Thus, utilities should continue to achieve an appropriate allocation of their effort between cost reduction, reduced losses and improved quality of service.

References

Arrindell, W.A. and van der Ende, J. (1985), "An Empirical Test of the Utility of the Observations-to-Variables Ratio in Factor and Components", *Applied Psychological Measurement*, 9 (2), 165-78.

Bentler, P.M. and Kano, Y. (1990), "On the Equivalence of Factors and Components", *Multivariate Behavioral Research*, 25 (1), 67-74.

Billinton, R. and Allan, R. (1984), *Reliability Evaluation of Power Systems*, London: Plenum Press.

Brown, R.E. (2002), *Electric Power Distribution Reliability*, New York: Marcel Dekker Inc.

CEPA (2003), "Cepa's Report on Benchmarking", ed. Ofgem, London: Cambridge Economics Policy Associates

Coelho, J., Nassar, S.M., Gauche, E., Ricardo, V.W., Queiroz, H.L., de Lima, M., and Lourence, M.C. (2003), "Reliability Diagnosis of Distribution System under Adverse Weather Conditions," *Power Tech Conference Proceedings, 2003 IEEE Bologna*, 4, 290-294.

Coelli, T., Rao, P.D.S., and Battese, G., eds. (2005), *An Introduction to Efficiency and Productivity Analysis*, Springer.

Domijan, A., Jr., Matavalam, R.K., Montenegro, A., and Willcox, W.S. (2003), "Analysis of Rain, Wind and Temperature Effects on Power Distribution Outages", *Proceedings of the IASTED International Conference, Power-Con - Special Theme: Blackout*, 44-48.

Domijan, A., Jr., Matavalam, R.K., Montenegro, A., Willcox, W.S., Joo, Y.S., Delforn, L., Dize, J.R., Davis, L., and Agostini, J.D. (2005), "Effects of Normal Weather Conditions on Interruptions in Distribution Systems", *International Journal of Power and Energy Systems*, 25 (1), 54-62.

DTI (2006), "Consultation on Resilience of Overhead Power Line Networks - An Energy Review Consultation", Department of Trade and Industry, London.

EDF (2003), "Edf Response: Electricity Distribution Price Control Review: Initial Consultation", July, EDF.

Engle, R.F. and Mustafa, C. (1992), "Modelling Peak Electricity Demand", *Journal of Forecasting*, 11, 241-51.

EPRI (2006), "Outline of Guide for Application of Transmission Line Surge Arresters-42 to 765kv, Extended Outline", Electric Power Research Institute.

Farrell, M.J. (1957), "The Measurement of Productive Efficiency", *Journal of Royal Statistical Society*, Series A (120), 253-90.

Franco, G. and Sanstad, A. H. (2008), "Climate Change and Electricity Demand in California," *Climatic Change*, 87 (Suppl 1), 139-51.

Giannakis, D., Jamasb, T., and Pollitt, M. (2005), "Benchmarking and Incentive Regulation of Quality of Service: An Application to the UK Electricity Distribution Networks", *Energy Policy*, 33 (1), 2256-71.

Gorsuch, R.L. (1990), "Common Factor-Analysis Versus Component Analysis - Some Well and Little Known Facts", *Multivariate Behavioral Research*, 25 (1), 33-39.

Hackney, J. (2002), "Increasing the Value of Weather Information in the Operation of the Electric Power System", Boulder, Colorado, Workshop Report, Environmental and Societal Impacts Group, National Center for Atmospheric Research.

Hor, C.L., Watson, S.J., and Majithia, S. (2005), "Analyzing the Impact of Weather Variables on Monthly Electricity Demand", *IEEE Transactions on Power Systems*, 20 (4), 2078-85.

House of Commons (2003), "Trade and Industry Committee Inquiry into the Resilience of the National Grid Network", in *Memorandum by Ofgem*, ed. House of Commons: House of Commons.

House of Commons (2004), "The Electricity Distribution Networks: Lessons from the Storms of October 2002 and Future Investment in the Networks", in *First Report of Session, 2004-2005, Trade and Industry Committee*: House of Commons.

IPCC (2000), "Special Report on Emission Scenarios", in *A special report of working group III of the Intergovernmental Panel on Climate Change, World Meteorological Organization and United Nations Environmental Programme*, ed. Cambridge University Press, Cambridge.

Jamasb, T. and Pollitt, M. (2001), "Benchmarking and Regulation: International Electricity Experience", *Utilities Policy*, 9, 107-30.

Jamasb, T. and Pollitt, M. (2007), "Incentive Regulation of Electricity Distribution Networks: Lessons of Experience from Britain", *Energy Policy*, 35 (12), 6163-87.

KEMA (2007), "Ofgem - Final Report: Review of Distribution Network Design and Performance Criteria", London: KEMA Consulting and Imperial College, London.

Kjolle, G.H., Seljeseth, H., Heggset, J., and Trengereid, F. (2003), "Quality of Supply Management by Means of Interruption Statistics and Voltage Quality Measurements", *European Transactions on Electrical Power*, 13 (6), 373-79.

Korhonen, P.J. and Syrjanen, P.J. (2003), "Evaluation of Cost Efficiency in Finnish Electricity Distribution", *Annals of Operations Research*, 121 (1-4), 105-22.

Langset, T. (2002), "Quality Dependent Revenues - Incentive Regulation of Quality of Supply", *Energy & Environment*, 13 (4-5), 749-61.

Li, X. and Sailor, D.J. (1995), "Electricity Use Sensitivity to Climate and Climate Change", *World Resource Review*, 7 (3), 334-46.

MET (2008), "Met Office Web Site: Learning Session."

Nillesen, P. and Pollitt, M. (2008), "Using Regulatory Benchmarking Techniques to Set Company Performance

Targets: The Case of Us Electricity", in *Cambridge Working Paper in Economics CWPE0834 / Electricity Policy Research Group EPRG0817*, Faculty of Economics, University of Cambridge.

Offer (1999), "Supply Interruptions Following the Boxing Day Storms 1998", Offer.

Ofgem (2004), "Electricity Distribution Price Control Review - Initial Proposal", Ofgem.

Ofgem (2004a), "Executive Summary to Consumer Survey, Consumer Expectations of DNOs and WTP for Improvements in Service Report," Accent Marketing & Research, London.

Ofgem (2004b), "Electricity Distribution Price Control Review - Final Proposals," Ofgem.

Ofgem (2004c), "Electricity Distribution Price Control Review, Update Paper," Ofgem.

Ofgem (2006), "2005-06 Electricity Distribution Quality of Service Report," London, U.K., Ofgem.

Prado, A., Meneu, V., and Valor, E. (2002), "Temperature and Seasonality Influences on Spanish Electricity Load," *Energy Economics*, 24, 55-77.

Prospect (2004), "Electricity Distribution Price Control Review: Initial Proposals - Prospect Response," Prospect.

Sailor, D.J. and Munoz, J.R. (1997), "Sensitivity of Electricity and Natural Gas Consumption to Climate in the U.S.A.: Methodology and Results for Eight States", *Energy*, 22 (10), 987-98.

Steiger, J.H. (1990), "Some Additional Thoughts on Components, Factors, and Factor Indeterminacy", *Multivariate Behavioral Research*, 25 (1), 41-45.

Valor, E., Meneu, V., and Caselles, V. (2001), "Daily Air Temperature and Electricity Load in Spain", *Journal of Applied Meteorology*, 40 (8), 1413-21.

Velicer, W.F. and Jackson, D.N. (1990), "Component Analysis Versus Common Factor Analysis: Some Issues in Selecting an Appropriate Procedure", *Multivariate Behavioral Research*, 25 (1), 89-95.

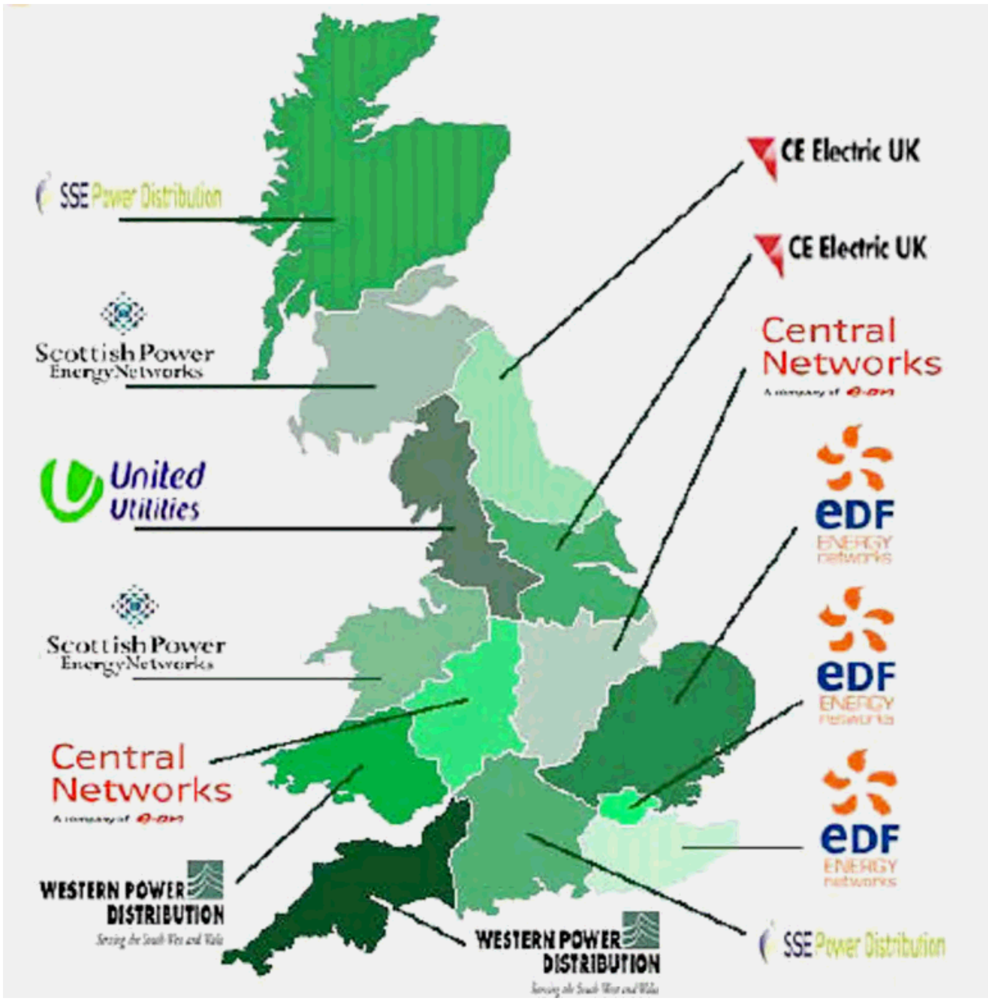
Widaman, K.F. (1990), "Bias in Pattern Loadings Represented by Common Factor Analysis and Component Analysis", *Multivariate Behavioral Research*, 25 (1), 89-95.

Yang, H. and Pollitt, M. (2008), "Incorporating Both Undesirable Outputs and Uncontrollable Variables into Dea: The Performance of Chinese Coal-Fired Power Plants", *European Journal of Operational Research*, (forthcoming).

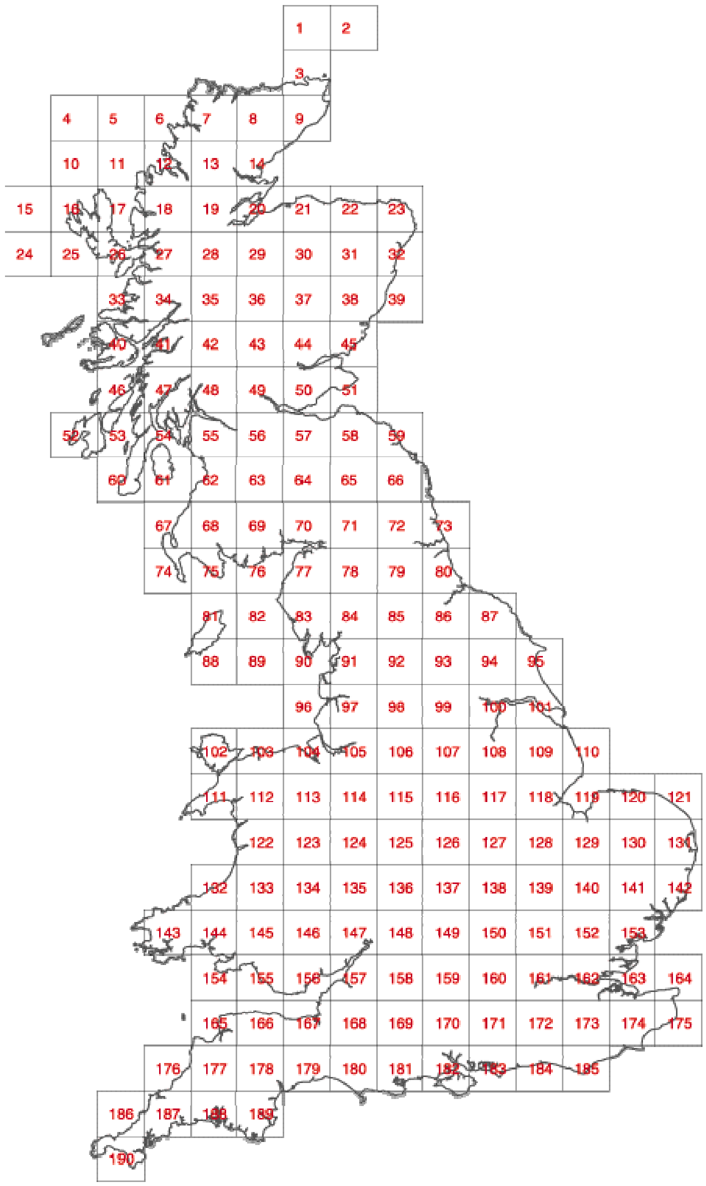
Yu, W., Jamasb, T., and Pollitt, M. (2007), "Incorporating the Price of Quality in Efficiency Analysis: The Case of Electricity Distribution Regulation in the U.K.", in *Cambridge Working Papers in Economics CWPE 0736/* Electricity Policy Research Group EPRG0713 July, Faculty of Economics, University of Cambridge.

Zhou, Y., Pahwa, A. , and Yang, S.S. (2006), "Modelling Weather-Related Failures of Overhead Distribution Lines," *IEEE Transactions on Power Systems*, 21 (4), 1683-90.

Appendix I



Service Areas of DNOs
Source: Ofgem Quality of Service Report 2003/04



MORECS (Met Office Rainfall and Evaporation Calculation System) Map
Source: UK MET Office