Comparison of electricity reliability satisfaction models using administrative data

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Abstract

Electricity system reliability is a public good that governments provide based on an estimate of the cost of power system interruptions, measured as the Value of Lost Load (VoLL). A variety of different estimation methods exist that typically trade off accuracy for cost, so government valuation studies include a mix of them. This project proposes a new method using a published administrative dataset that has recently become available. The dataset can replicate the basic model of consumer satisfaction and therefore is a useful proof-of-concept for this approach to be included in future valuations of electricity security of supply.

Word count: 2869

All code is available in R at https://github.com/bertiegyenes/DNO_interruptions

Introduction

Electricity security of supply includes a series of different concepts with context-dependent definitions based on the temporal and spatial scale, ranging from long-term fossil fuel dependence to second-by-second frequency control (Ang et al., 2015).

Capacity adequacy is a key component of security of supply – the total available supply capacity must always exceed or equal the capacity demanded due to the physical properties of the electricity system (Laponche, B., Tillerson, K., 2001). Capacity adequacy is a public good: it is non-excludable, as all electricity consumers automatically have it, and it is non-rival, as a single consumer cannot meaningfully reduce it for others (Kiesling & Giberson, 2004). As a public good, the market will not provide the equilibrium value of capacity adequacy in a perfectly competitive market (Varian, Hal R., 2019). The electricity wholesale market is not always a perfectly competitive environment: demand is highly inelastic in the short term, so suppliers are able to charge above their marginal costs in tight periods when total demand is close to the total available supply (Kirschen, D., Strbac, G., 2018). In theory, this economic rent may be enough to provide the level of capacity adequacy demanded by the market. In practice, this faces two key issues, leading to the so-called 'missing money' problem (DECC, 2014; Joskow, 2013; Kleit & Aagaard, 2022). First, tight periods allowing economic rent are rare and unpredictable in their size, so the associated projected revenue stream is uncertain. Risk-averse investors will therefore find it difficult to finance large, expensive and long-lasting projects in practice. Second, charging beyond marginal costs is perceived to potentially attract the attention of the energy regulator who may decide to act against any abuse of the market by imposing a price cap below the price necessary for the investment to break even.

Governments must therefore step in to correct for the market failure. Any economic policy providing capacity adequacy requires monetary value associated with interruptions, this is referred to as the Value of Lost Load (VoLL), typically measured in £/MWh. As electricity is a complementary good to many other goods and services (as an input to both their production and consumption), any interruption to it will have costs well beyond the marginal cost of electricity produced (Rutledge, I., Wright, P., 2011). VoLL can be estimated in different ways, including using macroeconomic models of the production function (any power interruption will lead to a loss of Gross Value Added and therefore will appear in national statistics) and direct costs studies where individuals assess the cost of several different scenarios (Schröder & Kuckshinrichs, 2015). Some methods are more suited for particular consumer groups: residential consumers' VoLL is often based on stated-preference surveys of consumer willingness to pay/avoid (Beenstock et al., 1998; Kim et al., 2014; London Economics, 2013; Praktiknjo, 2014). In practice, countries use a single VoLL value in a bidding zone (typically covering an entire country, as using different values for different consumers would be technically difficult in practice (London Economics, 2013; Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the Internal Market for Electricity (Text with EEA Relevance.), 2019). Extensive literature exists showing how VoLL varies according to a number of factors (location, business needs, time of day and many others – all cited evaluations in this section cover a variety of factors), but differences are assumed to be small, at least on any scale large enough for price differentiation, such as between regions, so a single weighted average is used in practice (DECC, 2013).

Using surveys to derive VoLL is not without issues. Some are theoretical: consumers may find it difficult to value an outage in different scenarios, or they may have an incentive to overstate its value. To tackle this, some studies have conducted surveys after actual blackouts (Billinton et al., 1993; Weijnen, M.P.C. & Ajodhia, V.S., 2006) but this approach faces practical issues, as large-scale blackouts are rare and surveys of this kind are expensive to conduct (London Economics, 2013; Schröder & Kuckshinrichs, 2015). An annual administrative dataset on smaller interruptions may be able to tackle both issues, as this would be informed by real outages and it would be readily available (so its use in a different context would be much cheaper than conducting a separate survey). If existing models of consumer satisfaction can be replicated with such a dataset, it could then be used to inform VoLL estimates, just like other survey-based methods are used to do so. The VoLL estimate is used in several parts of a government economic policy to deliver capacity adequacy, most importantly to set the level of reliability to for the policy to deliver (DECC, 2013, 2014; London Economics, 2013). Some assumptions on consumer satisfaction are included in the policy implicitly, such as setting a single payment schedule for the policy across a country and not differentiating between regions or consumers. A VoLL estimation method based on annual data could be used to update the VoLL-linked values included in the policy more frequently. If the dataset has the appropriate consumer- or region-level granularity, it could also inform different price schedules for different consumers. Both could send a more accurate market signal to consumers and investors, leading to a more efficient market, and reduce overall prices to consumers.

Short, localised interruptions happen all the time, all across Great Britain[1]. The independent energy regulator, the Office of Gas and Electricity Markets (Ofgem), has required Distribution Network Operators (DNOs) to report annually on the level of interruptions within their licence areas since the early 2000s. Since the mid-2010s, DNOs have also been required to report customer satisfaction on interruptions every year.

Rationale

The purpose of the project is to provide the proof-of-concept for a new method to estimate VoLL using administrative data on small interruptions published by Ofgem by answering two research questions. First, the project will seek to replicate the basic consumer satisfaction model: is there a negative relationship between the levels of interruption and consumer satisfaction? Establishing this would mean that it is possible to derive a new estimation method using administrative data. Second, the project will aim to show that the dataset has enough granularity to show regional differences: is there an interaction between regions and the levels of interruptions in determining consumer satisfaction? If this is the case, the estimation method would demonstrate a key potential advantage when considered in future valuations of VoLL.

Data

Distribution network operators (DNOs) function as regulated monopolies whose revenues are controlled by Ofgem according to the RIIO principle: Revenues = Incentives + Innovation + Output. Interruptions-related payments are the key component of the Incentives pillar and Ofgem prescribes detailed recording duties for the DNOs within the Regulatory Instructions and Guidance (RIG) documents (Office of the Gas and Electricity Markets Authority, 2015a). Performance metrics are provided annually as part of the RIIO-1 Electricity Distribution Annual Reports (Office of the Gas and Electricity Markets Authority, 2022), this is the data source used in this report.

Two metrics have been used to directly measure interruptions for many years: Customers Interrupted (CI) and Customer Minutes Lost (CML). For the purposes of this project, CML is used, as this includes a time component: it is defined as the mean time a customer had their supply

[1] England, Wales and Scotland share the same electricity system, while Northern Ireland is part of the Irish grid.

interrupted for in a year (Office of the Gas and Electricity Markets Authority, 2015b), therefore its units are minutes/year. As a well-established metric, CMLs for different DNOs are comparable.

The CML performance metric displays a symmetric distribution with almost identical mean and median (35.1 minutes/year and 34.8 minutes/year, respectively), and a large sample standard deviation (10.2 minutes/year) which should help when fitting linear regression. No clear time dependence is observed in Figure 1A that would hold across all DNOs, and Figure 1B shows no clear skew or outliers – in fact, CML is normally distributed (Jarque-Bera test, p=0.68).

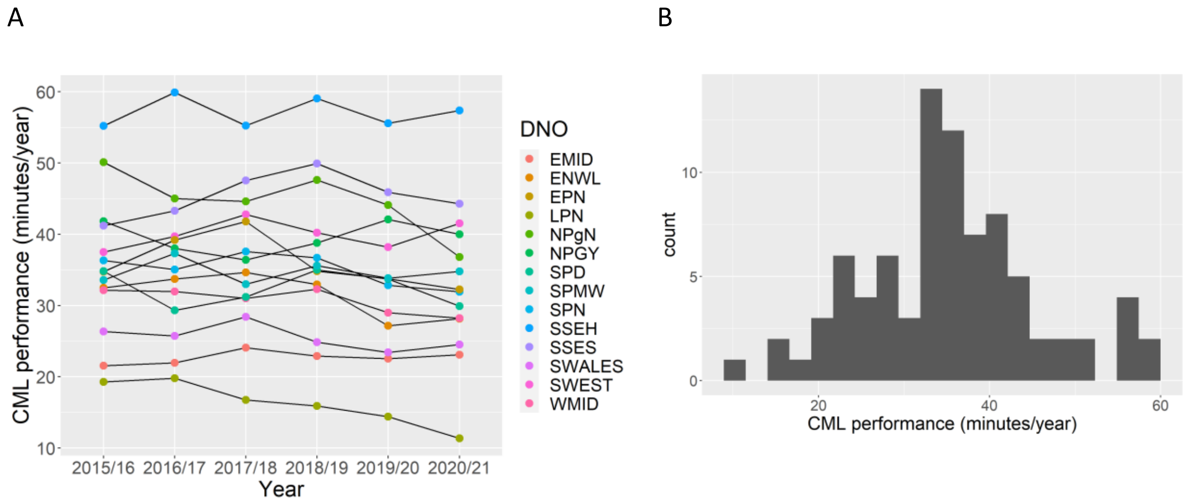

Figure 1. Customer Minutes Lost (minutes/year) performance distribution over time and across different DNOs. A) Time has no clear impact on CML performance across DNOs. B) CML performance histogram across all observations does not show outliers.

Customer satisfaction was introduced to the Incentives pillar in 2015 with DNOs expected to meet several pre-determined targets, including CML, in order to receive payment. All DNOs must commission the same third party to conduct the same survey – this is provided by Ofgem (Office of the Gas and Electricity Markets Authority, 2015c). The surveys are conducted on a random sample of consumers (both households and businesses) who have either contacted their DNO or been contacted by it in relation to an interruption, and includes a series of questions (Annex H is available as a data attachment to this project and includes the survey). Sample sizes are not available but the surveys must be powered to achieve a small relative standard error (3%) across all DNOs. Overall customer satisfaction scores are then calculated as the mean of several questions (1 – very dissatisfied, 10 – very satisfied).

The customer satisfaction score on interruptions has some outliers but it has identical mean and median (8.9/10). The sample standard deviation is considerably smaller than for the CML performance metric at 0.24. Figure 2A shows that most DNOs show an increase in the variable over time, so the regression analysis should include a time variable.

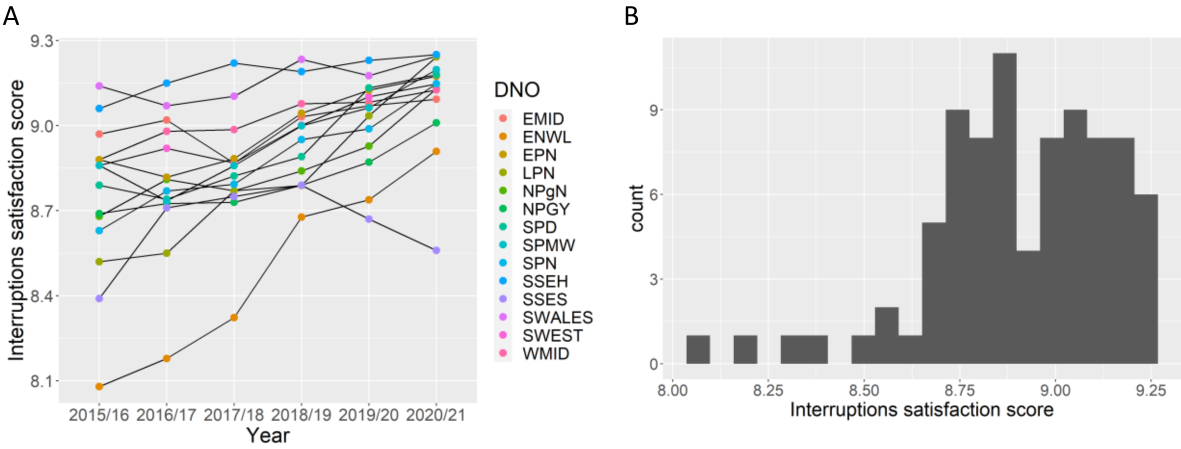

Figure 2. Customer satisfaction score (# out of 10) on interruptions over time and across different DNOs. A) Time dependence can be observed across DNOs. B) Satisfaction score histogram across all observations shows a few outliers.

The functional form of the relationship between variables is informed by the scatterplot between the key variables in Figure 3 (see Supplementary Table 1 for the names of DNOs). The overall relationship between the two continuous variables appears to be negatively correlated, so the estimated coefficient for CML is likely going to be negative. Most DNOs seem to cluster around particular areas in the graph, implying that there is potential value in including them as dummy variables. As expected from Figure 2B, there is less variation in data available in the lower range of the satisfaction scores, anticipating potential issues with the regression residuals in this range.

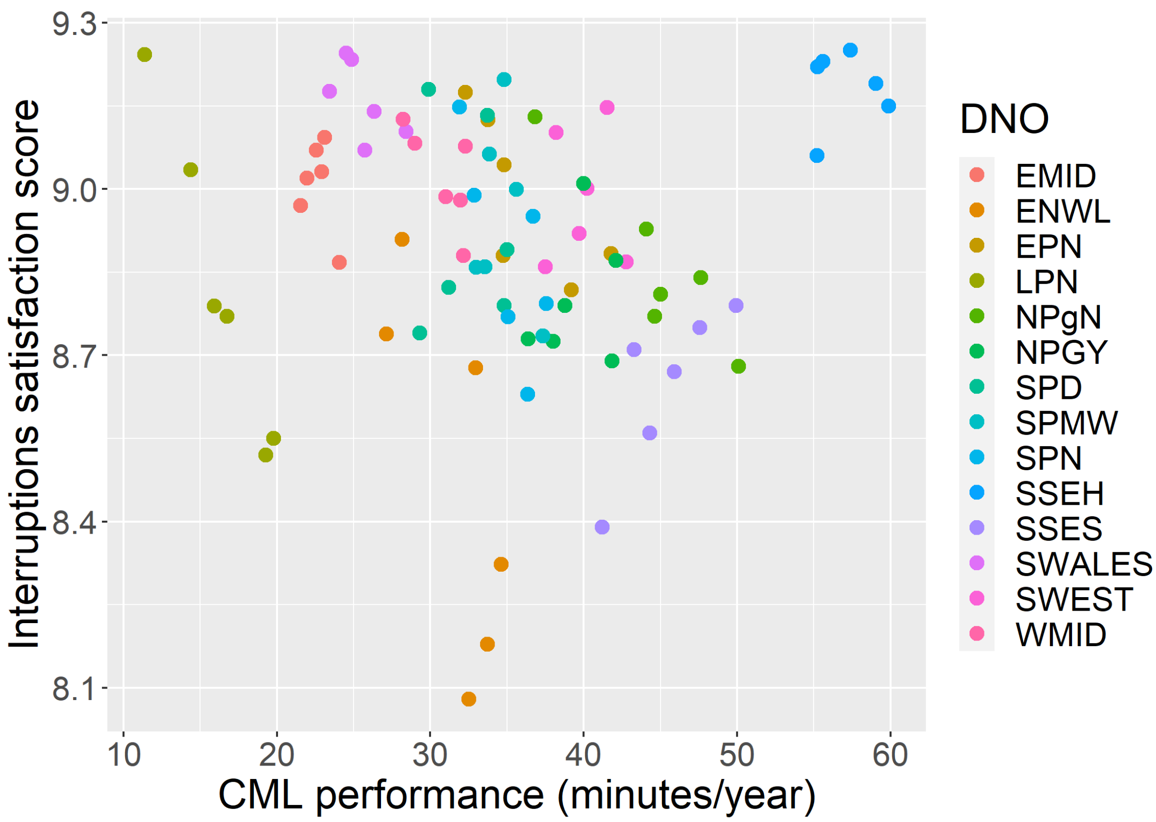

Figure 3. Scatterplot between the CML performance metric and the customer satisfaction score on interruptions.

Analysis

The direction of causation between the two continuous variables is straightforward to establish, as customer satisfaction surveys ask about prior interruptions: it is reasonable to expect CML to be the exogenous variable with the satisfaction scores being endogenous in the first instance. It is worth noting that the RIIO scheme sets targets for both metrics, therefore future work should cover the effect of these targets on the metric performance. Over time, it is also theoretically possible for the DNOs to target a particular level of CML in response to prior customer satisfaction performance. However, the impact of these two effects is likely limited for three reasons: electricity distribution networks are complex enough that any substantial work would have a large enough variation in impact that such finetuning to targets is not possible in practice, Ofgem adjusts the targets based on prior performance so that backtracking is not possible, and hitting CML performance targets has much larger associated incentive payments than customer satisfaction performance.

Two basic models of consumer satisfaction of electricity supply interruptions will be tested and compared. Governments essentially assume Model 1 when setting a single VoLL for an entire country, while Model 2 incorporates knowledge that VoLL depends on other factors, in this case on the consumers in different DNO areas.

Model 1:

$$satisfaction\ score = \alpha + \beta * CML + \gamma * t + u$$

Model 2:

$$\begin{aligned} satisfaction\ score &= a + b_1 * DNO_1 * CML + b_2 * DNO_2 * CML + \cdots + b_{13} * DNO_{13} * CML + c * t \\ &+ d_0 * CML + d_1 * DNO_1 + d_2 * DNO_2 + \cdots + d_{13} * DNO_{13} + w \end{aligned}$$

where $\alpha, \beta, \gamma, a, b_1, b_2, \dots, b_{13}, c, d_0, d_1, d_2, \dots, d_{13}$ are the regression coefficients, CML is customer minutes lost in minutes/year, t is time in years, $DNO_1, DNO_2, \dots, DNO_{13}$ are binary dummy variables to incorporate the DNOs as categorical variables (EMID – East Midlands is the reference category), and u, w are error terms. As the dependent variable is identical and the same dataset is used for both estimations, the model performance metrics are directly comparable. Restricted testing is also possible with the following null hypothesis: there is no interaction with DNO area when regressing the average interruption level (measured in CML) on consumer satisfaction score.

Diagnostic tests on the residuals for the two estimated models confirms homoskedasticity, linearity and appropriate functional forms (Table 1). However, Model 1 displays serial correlation, likely caused by the low sampling variation in certain ranges of the variables, so its estimated parameter coefficients would need robust standard errors if this model is explored further. Neither model has normally distributed residuals but as the sample size is relatively large (84 observations), the Central Limit Theorem means that the estimated coefficients can be assumed to be normally distributed and can be tested accordingly.

	Model 1	Model 2
Breush-Pagan test, p value	0.185659	0.116395
Durbin-Watson test statistic (p value)	1.408752 (0.004)	1.539522 (0.058)
Ramsey RESET, p value	0.851203	0.248156
Jarque-Bera test, p value	2.45E-05	1.59E-06

Table 1. Results of diagnostic tests for the two models

Both models have a significantly better fit than an empty model (p values for the null model F-test well below 0.05) but model performance metrics show Model 2 performing much better than Model 1 (Table 2). Model 2 has a lower residual standard error, and the adjusted R squared is also larger – almost 90% of the variation in consumer satisfaction scores is explained by the model compared to only about a quarter of it in the other model. The additional variables include valuable additional information as evidenced by the significant F-statistic from the restricted least squares testing and the lower AIC value.

	Model 1	Model 2
Adjusted R squared	0.256	0.878
Residual standard error	0.206	0.0836
F-statistic (df1, df2, p)	15.2 (2, 81, 2.40E-06)	22.2 (28, 55, 5.08E-21)
AIC	-22.1	-154
Restricted testing F-statistic (p value)	16.8 (7.84E-18)	

Table 2. Comparison of model performance metrics

The estimated parameters of Model 2 can be used to interpret the model in more detail (Table 3). As expected, CML has a statistically significant negative coefficient when other confounding factors are accounted for using other variables: 10 additional minutes of interruptions to the average consumer annually would lead to an average drop by about 1 in the consumer satisfaction score (-0.095 * 10 ≈ -1), all else held equal. However, many of the individual DNOs show significant differences in the average satisfaction scores compared to what the model would otherwise predict. For example, for a given CML performance, consumers in Southern England would score their DNOs performance 3.6 lower than consumers in the East Midlands reference category, while consumers in Yorkshire and the West Midlands would score them 2.7 lower. Some DNOs also have an impact on the slope associated with the CML relationship, as shown by significant estimated interaction parameters. Taken together with the overall CML coefficient, some DNOs do not appear to be responsive to changes in CML at all (for example the Sottish DNOs, North Scotland: 0.094-0.095=-0.001, South Scotland: 0.1-0.095=0.005) or have a positive relationship (for example South Wales: 0.110-0.095=0.015). The latter would imply that additional interruptions would lead to higher satisfaction scores, therefore further analysis is required.

	Estimate (standard error)		Estimate (standard error)
(Intercept)	-109.5 (13.0) ***	Year	0.060 (0.006) ***
East Midlands	*(reference category)*	CML	-0.095 (0.043) *
North West	-1.017 (1.056)	CML: North West	0.042 (0.045)
East Anglia	-1.623 (1.047)	CML: East Anglia	0.080 (0.044)
London	-1.480 (0.997)	CML: London	0.042 (0.045)
North East	-1.763 (1.054)	CML: North East	0.083 (0.044)
Yorkshire	-2.695 (1.168) *	CML: Yorkshire	0.104 (0.046) *
South Scotland	-2.387 (1.083) *	CML: South Scotland	0.100 (0.045) *
Merseyside and North Wales	-1.442 (1.264)	CML: Merseyside and North Wales	0.073 (0.049)
South East	-1.434 (1.154)	CML: South East	0.071 (0.046)
North Scotland	-1.930 (1.418)	CML: North Scotland	0.094 (0.046) *
Southern	-3.600 (1.100) **	CML: Southern	0.119 (0.044) **
South Wales	-2.386 (1.133) *	CML: South Wales	0.110 (0.049) *
South West	-1.492 (1.218)	CML: South West	0.078 (0.046)
West Midlands	-2.695 (1.206) *	CML: West Midlands	0.113 (0.049) *

Table 3. Estimated coefficients for model parameters. CML is customer minutes lost in minutes/hour, Year is the numerical value for the year, DNOX are dummy variables for each DNO, CML:DNOX are the interaction terms between CML and each DNO. Standard errors are included in parenthesis, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Discussion

Consumers in different DNOs have different attitudes to interruptions and a single national Value of Lost Load is not an accurate description of the system. The project clearly shows a negative relationship between levels of interruption and consumer satisfaction, answering the first research question positively. The analysis is therefore a successful proof-of-concept that publicly available administrative data can be used to replicate much larger and more expensive studies. The second research question also holds, there is an interaction between regions and levels of interruptions, but this has some key caveats.

The model presented in this report has several limitations. Mean length of total interruptions is a good general measure of interruptions but others exist. Research has suggested that consumers also care about when an interruption takes place during the day, or how long it lasts, which is not directly measured in CML (Kim et al., 2014; London Economics, 2013). Published data includes a breakdown between planned and unplanned CML, but no other metric is publicly available. However, DNOs must submit details of each interruption to Ofgem, so this dataset may be used to derive additional metrics informed by existing literature. Prior performance may also have an anchoring effect when consumers respond to surveys, so a lagged measure is worth exploring.

The satisfaction scores also have shortcomings. The survey specified by Ofgem includes questions that are less focused on the levels of interruptions and more on how the interruptions are handled by DNOs once they have taken place – it would be beneficial to exclude these from the overall score.

Finally, the model only shows that DNOs have an impact on consumer satisfaction without details on how this arises, resulting in two main issues. First, it is unclear what the surveys are actually measuring in different DNOs. While Ofgem specifies the parameters of the survey collections in detail, some differences between DNOs cannot be accounted for in this way, for example general attitudes to surveys and the consumer population size. Multilevel modelling may be a natural next step to incorporate these effects in a systematic way. Second, the model does not reveal what characteristics of DNOs are responsible for the relationship with interruptions. Many options are possible to explore: for example, different consumer groups have different attitudes to interruptions – in particular, small and medium enterprises (SMEs) have a particularly high Value of Lost Load, as they cannot switch to a different power supply and an interruption causes financial damage due to stalled production (London Economics, 2013; Praktiknjo et al., 2011). Future work could use the rate of SMEs in different regions to explore this.

In conclusion, the new estimation method is not yet ready for operationalisation and assigning different VoLL to different DNOs in government economic policies. For example, the lack of granularity to the actual cause of the effect means that some DNOs appear to prefer higher levels of outages. However, if these issues are resolved, it may be possible to incorporate cheap administrative data when setting VoLL in order to create more accurate price signals and therefore to make government policies more economically efficient.

Bibliography

Ang, B. W., Choong, W. L., & Ng, T. S. (2015). Energy security: Definitions, dimensions and indexes. *Renewable and Sustainable Energy Reviews*, *42*, 1077–1093. https://doi.org/10.1016/j.rser.2014.10.064

Beenstock, M., Goldin, E., & Haitovsky, Y. (1998). Response bias in a conjoint analysis of power outages. *Energy Economics*, *20*(2), 135–156. https://doi.org/10.1016/S0140-9883(97)00017-0

Billinton, R., Tollefson, G., & Wacker, G. (1993). Assessment of electric service reliability worth. *International Journal of Electrical Power & Energy Systems*, *15*(2), 95–100. https://doi.org/10.1016/0142-0615(93)90042-L

DECC. (2013). *Annex C: Reliability Standard Methodology*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/223653/emr_consultation_annex_c.pdf

DECC. (2014). *Electricity Market Reform—Capacity Market Impact Assessment*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/324430/Final_Capacity_Market_Impact_Assessment.pdf

Joskow, P. L. (2013). Symposium on 'Capacity Markets.' *Economics of Energy & Environmental Policy*, 2.

Kiesling, L., & Giberson, M. (2004). *Electric Network Reliability as a Public Good*. 7.

Kim, C.-S., Jo, M., & Koo, Y. (2014). Ex-ante Evaluation of Economic Costs from Power Grid Blackout in South Korea. *Journal of Electrical Engineering and Technology*, *9*(3), 796–802. https://doi.org/10.5370/JEET.2014.9.3.796

Kirschen, D., Strbac, G. (2018). *Fundamentals of Power System Economics* (Second). John Wiley & Sons, Inc.

Kleit, A. N., & Aagaard, T. S. (Eds.). (2022). Reliability and the Missing Money Problem. In *Electricity Capacity Markets* (pp. 37–53). Cambridge University Press. https://doi.org/10.1017/9781108779159.004

Laponche, B., Tillerson, K. (2001). The green paper "towards a European strategy for the security of energy supply." *Revue de l'Energie*, *529*, 425–431.

London Economics. (2013). *The Value of Lost Load (VoLL) for Electricity in Great Britain*. https://www.ofgem.gov.uk/sites/default/files/docs/2013/07/london-economics-value-of-lost-load-for-electricity-in-gb_0.pdf

Office of the Gas and Electricity Markets Authority. (2015a). *RIIO-ED1 electricity distribution price control – overview of the regulatory instructions and guidance*. https://www.ofgem.gov.uk/publications/direction-make-modifications-regulatory-instructions-and-guidance-rigs-riio-ed1-version-50

Office of the Gas and Electricity Markets Authority. (2015b). *RIIO-ED1 regulatory instructions and guidance: Annex A – Glossary*. https://www.ofgem.gov.uk/publications/direction-make-modifications-regulatory-instructions-and-guidance-rigs-riio-ed1-version-50

Office of the Gas and Electricity Markets Authority. (2015c). *RIIO-ED1 regulatory instructions and guidance: Annex H – Customer Service*. https://www.ofgem.gov.uk/publications/direction-make-modifications-regulatory-instructions-and-guidance-rigs-riio-ed1-version-50

Office of the Gas and Electricity Markets Authority. (2022). *RIIO-ED1 Network Performance Summary 2020-21*. https://www.ofgem.gov.uk/publications/riio-1-electricity-distribution-annual-report-2020-21

Praktiknjo, A. J. (2014). Stated preferences based estimation of power interruption costs in private households: An example from Germany. *Energy*, *76*, 82–90. https://doi.org/10.1016/j.energy.2014.03.089

Praktiknjo, A. J., Hähnel, A., & Erdmann, G. (2011). Assessing energy supply security: Outage costs in private households. *Energy Policy*, *39*(12), 7825–7833.

Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity (Text with EEA relevance.), 158 OJ L (2019). http://data.europa.eu/eli/reg/2019/943/oj/eng

Rutledge, I., Wright, P. (Ed.). (2011). *UK Energy Policy and the End of Market Fundamentalism*. Oxford University Press.

Schröder, T., & Kuckshinrichs, W. (2015). Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review. *Frontiers in Energy Research*, *3*. https://www.frontiersin.org/article/10.3389/fenrg.2015.00055

Varian, Hal R. (2019). *Intermediate Microeconomics: A Modern Approach* (Ninth). W. W. Norton.

Weijnen, M.P.C. & Ajodhia, V.S. (2006). Regulation beyond price. In *None (EN)*. http://resolver.tudelft.nl/uuid:f6d697f7-746b-4a43-9070-4c61ac118d1a

Appendix

DNO acronym	**DNO licence area**
ENWL	North West England
NPgN	North East England
NPgY	Yorkshire
WMID	West Midlands
EMID	East Midlands
SWALES	South Wales
SWEST	South West England
LPN	London
SPN	South East England
EPN	East Anglia
SPD	South Scotland
SPMW	Merseyside and North Wales
SSEH	North Scotland
SSES	Southern England

Supplementary Table 1. DNO acronyms and corresponding licence areas