



# Resilience performance of smart distribution networks

Low Carbon London Learning Lab



Report D4

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## Executive summary

This report investigates the reliability of demand side technologies for network constraint management. It consists of three parts; the first two consider two network management technologies that have been trialled extensively within the LCL programme: residential demand response mediated by dynamic time-of-use (dToU) signals, and the demand side response (DSR) of industrial and commercial (I&C) customers in response to load control signals. The third and final part considers network reliability performance when generation and demand led DSR is used to substitute for network reinforcement. In this context a number of alternative methods for integrating network reliability into effective capacity figures for I&C DSR assets are presented and discussed.

### Residential dynamic time of use

In Chapter 2, this report discusses the effects of dynamic time of use tariffs on network constraint management. It builds on the work of report A3 [1], which established mean observed responses for a range of customer and event types. The present report develops further statistical analysis of the residential dToU trial data in order to establish predictive response models and quantify the effect of dToU signals on network capacity requirements for residential customers.

Constraint Management dToU trials were performed as part of the LCL programme, in order to test the ability to reduce residential demand during times of peak load. Responses varied significantly across events during the trial year 2013, with values from 26W/household to 72W/household. This report has identified two simple empirical models to explain this variability. The models are consistent with the observations and may be used to guide expectations for future events.

The simplest model is that of an average demand reduction that is proportional to the overall demand level, within a range of 7.1%-8.4% (95% confidence level). It should be noted this range represents the average *expected* behaviour of future events, but from the DNO perspective it is critical to identify the range of responses for a *single* future event. The same model predicts future events to result in demand reductions in the range 4.6%-11.0% (95% confidence level).

An alternative model is that of an expected demand response magnitude that decreases linearly with the outside temperature at the time of the event. Confidence intervals are also derived for single and mean predictions from this model. It must be noted that these models are neither causal nor complete, and future observations from similar trials and commercial rollout of dToU tariffs will allow for refinement of the models developed here. In this regard we note that the observed performance is consistent with a slight reduction in demand response magnitude over the course of the trial (novelty effect), but this trend coincided with decreasing baseline demand and increasing temperatures, which means the evidence for this effect is weak.

The report proceeds to consider the use case where the DNO arranges for high-price signals to be broadcast to a set of households in order to alleviate network constraints. An essential step in this process is the quantification of the expected capacity contribution due to the dToU signal. It is demonstrated that the capacity contribution of demand response can be decomposed into two components: *mean response* and *variance response*. The variance response results from changes in the variance of consumption levels between households. In the case of the LCL constraint management trials, the high-price signal was always found to *reduce* the variance of household consumption levels, even more than suggested by the mean load reduction. This is consistent with trial participants opting

to switch off or postpone the use of discretionary large loads, thus reducing the propensity of large load peaks. The variance response thus has the effect of boosting the capacity contribution of demand response, as a lower capacity margin is required to anticipate peak load fluctuations.

To get an impression of the impact that the variance reduction effect has on the capacity contribution, its value was computed across a range of aggregation levels. In all cases the variance contribution boosted the capacity contribution, but by an amount that decreases with the aggregation level. A maximum boost of 25% relative to the mean response was observed at a mean demand response capacity contribution of 50 kW (approx. 500-1500 households), decreasing to 10% at 1 MW (approx. 15,000-35,000 households) and 5% at 10 MW. These are significant figures, but they are outweighed by the observed variability in the mean response itself, with fluctuations of 40% or more around the expected value. Therefore, in most cases, the additional contribution of variance response may be ignored without material consequence.

Finally, the report considers potential conflicts between the DNO's local network management aims and the supplier's incentive to respond to wholesale electricity markets. At times of abundant wind power availability, the suppliers may broadcast low prices to consumers in order to incentivise demand shifting. However, the resulting additional demand may boost local demand far above previously anticipated levels and thus interfere with network operations.

The extent to which demand may be boosted by low prices was analysed using data from the LCL Supply Following dToU trials. It was confirmed that there is a considerable risk of increasing the load on distribution networks, with 22 out of 48 low price events achieving load levels that are consistent with daily peak load or higher levels, and 10 of those showing load levels that are significantly higher than the baseline (to within 95% confidence). The enhanced load peaks all occurred on weekday evenings and weekend afternoons, but their occurrence does not appear to depend on the magnitude of the expected peak demand of the day. We note that these findings must be taken in the context of the trial: changes to the price signals may increase or reduce motivation to respond, while increased penetration of home automation may make it easier for consumers to respond at hitherto inconvenient times (e.g. sleeping or working hours).

### **Industrial & Commercial DSR**

In Chapter 3, this report analyses the reliability performance of I&C DSR as evidenced in the Low Carbon London trials. Whereas LCL report A7 [11] analysed the response of I&C sites from the perspective of the aggregators (contract terms) and the dispatch process, the present report quantifies their contribution to network constraint management using probabilistic models and methods.

A qualitative assessment of the response traces revealed that the variability, magnitude and seasonal dependence of I&C DSR was distinctive for the classes considered: diesel, CHP (combined heat and power), HVAC (heating, ventilation and air-conditioning) and water pumping stations. Generation-led DSR (diesel and CHP) was found to respond most in line with the contract targets, consistent with their direct control over generation levels. The response of demand-led DSR (HVAC and water pumping stations) is more variable, both in terms of average magnitude and the inter-event variation. Furthermore, HVAC sites demonstrated much larger response magnitudes – and variability – in the summer trials, than in the winter trials. This is consistent with the larger dependence on air conditioning in the summer months, allowing for larger reductions.

Probabilistic response models were constructed for each of the four DSR types, and separately for the summer and winter trials. For the construction of such probabilistic response models it is important that a significant fraction of sites outperformed the contract terms, with HVAC sites during summer showing the strongest performance, with reductions up to six times of the contracted amount. The decision whether to take this bonus into account in the models has significant implications for aggregate performance metrics.

One application of probabilistic response models is for determining the number of independent sites that are required to achieve a load reduction target with a certain minimum probability. Unit commitment diagrams are used to provide insight into the required number of sites as a function of response magnitude and desired confidence. In addition, an analytical approximation is introduced for the unit requirement curve, which may be used as a shortcut to performing numerical studies, especially when absolute accuracy is not required. For example, it may be used to develop an intuitive understanding of the impact of single-unit response parameters on aggregate behaviour, or to embed approximate dependability characteristics in a larger simulation.

Analysis of the response traces also evidenced the occurrence of simultaneous late-start events, involving sites being triggered by single aggregators. This reinforces the need to understand the potentially severe impacts of common mode failures, where failures can be traced back to a common root cause. The simplest example in this context is an event where an aggregator is unable to dispatch the DSR sites under its control, for example due to a failure in the communication network. This case was analysed numerically in a model, where  $N$  sites are distributed over a small number of aggregators. A probability of just 0.5% for the failure of an aggregator to activate its DSR sites has a very large impact on the unit commitment requirements. Depending on the desired confidence level, using a single aggregator may never provide sufficient dependability, whereas good performance is recovered with the use of three independent aggregators.

Finally, it has been noted that demand-led DSR may take the form of demand shifting, where the initial demand reduction is followed by a payback phase in which the load increases with respect to the baseline. If DSR is used for constraint management by the DNO, the payback effect may result in postponing rather than resolving the network constraint. In the LCL I&C DSR trials, payback peaks have been observed with a magnitude up to 8 times the contracted load reduction. The peak magnitude is highly variable, but generally characteristic for the site. It would seem reasonable for the DNO and aggregator to profile a site's 'payback signature' as part of the sign-up process, and perhaps subject it to contractual limitations.

### **Network-centric reliability modelling**

The present distribution network planning standard, Engineering Recommendation P.2/6 (ER P2/6) [38], specifies the demand restoration requirements following first and second circuit outages and hence drives network reinforcement and planning. In addition, ER P2/6 specifies a capacity contribution of distributed generation (DG) that can be used in network planning. Based on a range of successful demonstration and trials carried out in Low Carbon London project, UK Power Networks has developed a number of generation-led and demand-led Demand Side Response (DSR) schemes to substitute for network reinforcement. The capacity contribution of these DSR schemes is quantified following the philosophy of the present ER P2/6 used to calculate capacity contribution of DG.

The key objective of this section of the report is to assess the *reliability performance* of distribution network when DSR is used to defer network upgrades driven by load growth. Based on trials conducted in Low Carbon London, DSR contribution to security of supply is hence assessed using a probabilistic risk modelling framework to further inform a number of topics:

- Reliability contribution of DSR technologies in a network context
- Strengths and weaknesses of ER P2/6 in estimating contribution to security of supply
- Benefits of contractual redundancy
- Impact of DSR coincidence in delivery (common mode failures) on contribution to security<sup>1</sup>
- Impact of DSR scale / magnitude on contribution to security of supply.

The ER P2/6 approach applies reliability modelling of individual non-network technologies without considering the actual distribution network. Hence, the present approach offers limited insight into the actual reliability implications associated with the use of DSR in particular scenarios. The reason is that the reliability delivered to end consumers is ultimately driven by the reliability characteristic of both the actual network and DSR. One of the key objectives of this work is therefore to compare the levels of capacity contribution and the resulting network reliability performance that correspond to the following definitions established for network adequacy studies:

- Effective Load Carrying Capability (ELCC) is the amount by which the load may be increased in the presence of DSR facilities while the original risk is maintained
- Equivalent Firm Capacity (EFC) is the amount of capacity of always available source, which can replace DSR facilities while the supply risk is maintained
- Equivalent Network Capacity (ENC) is the increase in network capacity based on an equivalent circuit with the reliability performance of the real network, which can replace DSR facilities while the supply risk is maintained.

The current P2/6 methodology uses a concept of 'Equivalent Circuit Capacity (ECC)' with the assumption that the addition of new components (new circuits or new transformers) neither increases nor decreases the overall fault rate of the network. Each of the above methods for determining capacity credit of DSR facilities, including the method used in ER P2/6, is compared against the network capacity needed to ensure compliance with the security standard (' $N - 1$ ' for the scenarios considered). The approach is illustrated in Figure 1.

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<sup>1</sup> A practical example of a common mode failure might be an aggregator losing telecoms at their office, having a knock-on impact on the DSR sites that they were coaching through an event.

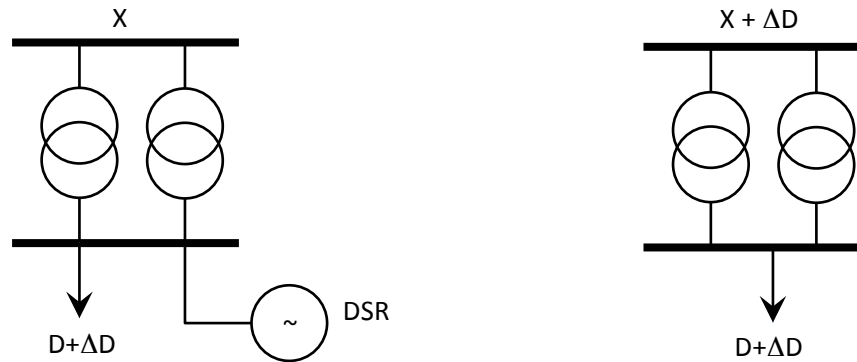


Figure 1: Illustration of the approach for comparison of different methods for capacity credit of DSR facilities

A network (capacity  $X$ ) and a DSR that supply Group Demand  $D + \Delta D$  are considered. Each of the capacity credit methodologies calculates a different value of  $\Delta D$ . We compare the reliability performance of DSR as calculated by the P2/6 alternative metrics (ELCC, EFC and ENC) against that of P2/6 to determine the equivalent network reinforcement. Key observations are as follows:

- The contribution of DSR to security of supply, as measured by the alternative metrics, depends on the reliability of the network (not considered in ER P2/6), as the capacity value allocated to DSR is linked with the equivalent network reinforcement that would be required to deliver a similar reliability of supply.
- In highly reliable networks (e.g. circuit failure rate 2% and MTTR<sup>2</sup> of 24 hours) the alternative methods hence allocate a much lower contribution to DSR and therefore would result in lower increase of Group Demand when compared with P2/6. On the other hand, the ENC method and ER P2/6 produce similar contributions in networks with low reliability (for example, a failure rate of 20% and MTTR of 240 hours).
- The contribution of DSR to security of supply, as measured by the alternative approaches, deliver relatively similar reliability performance as the philosophy of quantifying the capacity credit is based on the comparison with conventional network up-grades.
- The capacity contribution of DSR, as measured by the alternative approaches, reduces with increase in penetration level of DSR and with coincidence in delivery (common mode failure).
- The reliability delivered, measured by EENS<sup>3</sup>, is relatively stable for the alternative approaches when compared to the P2/6 approach. The EENS for the P2/6 approach depends significantly on (a) the volume of DSR when compared with the size of Group Demand and (b) the existence of common mode failure - effects that are ignored in the P2/6 approach. In this context, the reliability of the network with DSR, when capacity credit is determined by the ER P2/6 approach, is significantly lower than compared with other methods for deriving DSR capacity value, particularly in highly reliable networks. For example, in the case of the circuit failure rate being 2%, MTTR being 24 hours and with three DSR facilities, the EENS is more than 15 times larger than in the ENC method. In networks with lower circuit reliability the difference diminishes.
- If DSR facilities cannot run in islanding operation then the contributions calculated using the alternative metrics are zero (when the network is supplied by two circuits). It is assumed that

<sup>2</sup> Meant time to restore / repair

<sup>3</sup> Expected energy not supplied



demand under demand-led DSR can deliver its contribution even in islanding mode, as contracted demand can be interpreted as demand reduction.

The following recommendations can be made for the situation where DSR is used to defer distribution network upgrades driven by load growth:

- When applying the ER P2/6 approach to quantifying the contribution of DSR to security of supply, it is important to assess the impact on the reliability of supply, particularly in the context of the Interruption Incentive Scheme. Here, the alternative methods (ELCC, EFC and ENC) for quantifying capacity contribution of DSR provide useful insights.
- Consideration of diversity and common mode failures of DSR may be relevant when using DSR to substitute for network reinforcement.
- Contractual redundancy improves the probability of delivering the P2/6 contribution and may be considered in the context of the reliability of supply delivered to end customers.
- When evaluating the contribution to security of supply of DSR, the relative capacity of DSR to that of Group Demand should be considered.

Although this analysis identified a number of weaknesses of the present standard, ER P2/6 based-evaluation of the contribution of DSR, as carried out in [19] (which is then used to establish contracts with DSR following Low Carbon London Trials), is fully justified as ER P2/6 is the existing network standard and only available framework for quantifying capacity contribution of DSR. However, ER P2/6 will be fundamentally reviewed shortly and in the context of the work presented in this report, it will include consideration of costs of traditional and smart grid solutions (e.g. DSR) in enhancing network capacity and the corresponding benefits delivered to end consumers, so that a business case for alternative solutions to enhancing network capacity can be established.



## Glossary

|      |                                                            |
|------|------------------------------------------------------------|
| CDF  | Cumulative Density Function                                |
| CHP  | Combined Heat and Power                                    |
| CM   | Constraint Management [for residential dToU-tariff trials] |
| COPT | Capacity Outage Probability Table                          |
| DG   | Distributed Generation                                     |
| DR   | Demand Reduction                                           |
| DSR  | Demand Side Response                                       |
| dToU | Dynamic Time-of-Use                                        |
| ECC  | Equivalent Circuit Capacity                                |
| EENS | Expected Energy Not Supplied                               |
| EFC  | Equivalent Firm Capacity                                   |
| EFOR | Equivalent Forced Outage Rate                              |
| ELCC | Effective Load Carrying Capability                         |
| ENC  | Equivalent Network Capacity                                |
| I&C  | Industrial and Commercial customers                        |
| IEEE | Institute of Electrical and Electronic Engineers           |
| LDC  | Load Duration Curve                                        |
| LOLP | Loss Of Load Probability                                   |
| P2/6 | Engineering Recommendation P.2/6                           |
| PDF  | Probability density function                               |
| SF   | Supply-following [for residential dToU trials]             |

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# 1 Introduction

## 1.1 Background

Increasing penetration of renewable generation combined with the electrification of space heating and transportation will pose two major challenges to the electricity system:

- a) The variable output of renewable generation will significantly reduce the efficiency of demand-supply balancing if delivered by generation alone.
- b) Load growth characterised by a disproportionate increase in peak relative to overall energy consumption will necessitate significant network reinforcements, increasing the per unit cost of energy.

In a business as usual scenario that is built on a predict-and-provide philosophy this trend will necessitate costly investments in distribution assets [1].

The Low Carbon London project has trialled a range of technologies and techniques that have the potential to replace traditional asset-based solutions by ‘smart’ control-based solutions. The latter may allow for postponing or avoiding capacity upgrades, thus saving on capital investments. The first step in the appreciation of these control-based approaches is a quantification of their ability to change the power flows in the network and thereby reduce the need for physical capacity.

However, even if the case for smart control is readily made when considering the *average* performance of these technologies, there are concerns about their effects on reliability. Whereas the reliability of physical assets is well-understood and incorporated in security standards, this is not currently the case for smart grid solutions. Furthermore, physical assets provide their intended service by default, unless they are rendered inoperable by a fault, whereas responsive solutions must act in order to perform. These actions are thus exposed to a much larger set of failure modes, which need to be understood before smart grid technologies can be used in an optimal way without sacrificing reliability.

The present distribution network planning standard, Engineering Recommendation P2/6 (ER P2/6) [38], defines redundancy requirements of the distribution network and hence drives network reinforcement and planning. ER P2/6 specifies a capacity contribution of distributed generation (DG) that can be used in network planning, and the framework may be applied to demand response (DR) actions as well. Nevertheless, the philosophy behind P2/6 is fundamentally that of an asset-based system, and it merits careful consideration whether this can meaningfully be extended to cover DSR schemes.

## 1.2 Scope and objectives

This report aims to elucidate the benefits and risks of demand side technologies from the perspective of the DNO, with a focus on technical risks to the network resulting from capacity violations. The first two chapters consider in isolation two network management technologies that have been trialled extensively within the LCL programme. Chapter 2 considers the network capacity contribution of residential demand response, implemented via a dynamic time-of-use (dToU) tariff. Chapter 3 analyses the reliability of industrial and commercial (I&C) demand response, implemented via load reduction contracts that may be called on-demand during agreed time windows. Moving beyond the technology-specific analysis in the earlier chapters, Chapters 4 and 5 consider a network-centric reliability assessment of connected components and related effective capacity metrics. Studies are performed

using the LCL DSR trial data, and the results obtained with a variety of network-aware risk measures are compared with ER P2/6 effective circuit capacities.

Throughout this report quantitative analyses are performed based on measured data. However, due to the large breadth of the trials performed, many observations depend on few and highly variable data sources. Furthermore, the technologies being investigated are subject to constant evolution, both of a technical nature (meters, tariffs, controllers) and societal (experience, contractual, acceptance). Hence, the results from our analysis – although numerically precise – should be considered qualitative indications of results that are to be expected in future trials and other networks. Where sufficient data was available (the dToU trials), we have attempted to give an indication of the estimated accuracy of the results. Concepts and tools are introduced as required.

In addition to data-driven analysis, this report also attempts to qualify the effects of extreme events that have not been sufficiently observed, but are nevertheless considered important. These include common mode failures of I&C demand response (Chapter 3), and multi-circuit outages for network reliability analysis (Chapter 4 and 5). The objectives of this report are listed below.

Residential demand response:

- Quantify the observed dToU-mediated demand response in the LCL Constraint Management trials and derive a simple demand response model that is consistent with these observations.
- Establish a predictive model for Constraint Management demand response considering the statistical variation in event observations.
- Extrapolate the LCL CM results to arbitrary numbers of households and estimate the effective contribution to network margin that results from their response.
- Determine the resulting under- or overprovisioning factors for responses of a desired magnitude.
- Quantify the increase in observed demand levels due to low-tariff dToU signals, and its ability to drive aggregate consumption beyond the baseline daily peak.

Industrial and commercial demand response:

- Analyse observed responses in LCL I&C trials and construct probabilistic response models for different response classes (generation-led, demand-led response) and trials (summer, winter, additional).
- Define and compute credible response of N identical independent units.
- Determine contracting requirements depending on required response magnitude and confidence level.
- Develop an approximate 'summary model' for the dependable response of multiple units, which can replace simple linear F-factors.
- Analyse the hypothetical impact of common-mode failures that affect all sites controlled by a single aggregator.

Network integration:

- Establish necessary concepts, tools and risk indices for determining the reliability contribution of DSR technologies in a network context.
- Discuss strengths and weaknesses of ER P2/6 in estimating contribution to security of supply.

- Use the Low Carbon London DSR trial data in combination with network-centric reliability analysis to:
  - Quantify the benefits of contractual redundancy.
  - Determine the impact of DSR coincidence in delivery (common mode failures) on contribution to security.
  - Compute the impact of DSR scale / magnitude on contribution to security of supply.

### 1.3 Structure of the report

The remainder of the report is divided into three main sections that address different aspects of reliability in the smart grid paradigm. The results are summarised and discussed at the end of each section.

Chapter 2 focuses on dToU-mediated demand response of residential customers. The first part of this chapter considers the DNO's potential to reduce power consumption during peaks. To this end, the LCL dToU Constraint Management trials are re-analysed with a focus on variability and predictability of future events. The fluctuations of the observed demand response values are characterised to establish the intrinsic variability of this response, and a peak demand response model for the LCL dToU trial is fitted to the data.

The discussion then considers the more general problem of alleviating capacity constraints for an arbitrary number of households. The concept of network capacity contribution is introduced to quantify the contribution of dToU-DR to the effective network capacity, considering safety margins at predefined confidence levels. The effective demand response is computed for a range of household numbers and desired response magnitudes across all observed Constraint Management events, and over/under-provisioning requirements are computed.

The final section of chapter 2 investigates risks to the distribution network due to low-price dToU signals. When customers are incentivised to increase their consumption levels due to low and potentially negative wholesale electricity prices, this may trigger capacity constraints at the distribution level. In some conditions the resulting demand may significantly exceed the hypothetical daily peak demand that would have been observed in absence of the dToU signal. This section quantifies the observed low-tariff responses in the context of daily peak management.

Chapter 3 aims to establish a perspective on the reliability of I&C resources for network management. Events that were recorded as part of the LCL I&C trials are clustered into groups of similar sites (e.g. diesel vs. HVAC) and trial circumstances (summer vs. winter), and normalised in magnitude and duration to allow for cross-site comparison. Probabilistic models are established for each class, and these are used to compute the credible response of N identical independent units.

The resulting probabilistic models for N-unit responses are inverted to determine how many units are required to achieve a desired response magnitude at a given confidence level. This is graphically illustrated using *required commitment* curves, which are subsequently approximated by a simple model that allows for greater insight at very little computational cost. Finally, the need to model common-mode failures is established, and their effect on required commitment curves is computed.

Chapter 4 starts by establishing the necessary concepts, tools and risk indices for bottom-up probabilistic reliability analysis in a network context. As one of the key objectives of this work is to

compare the levels of capacity contribution and the resulting network reliability performance that correspond to the different definitions established for network adequacy studies, in addition to the P2/6 approach alternative concepts are introduced.

In chapter 5 these are applied to the probabilistic models for DSR contributions that were distilled from the LCL trials. The effective contributions to network security are computed for a number of scenarios across a range of network loading and reliability levels, and the results are compared with P2/6-derived equivalent circuit capacities.



## 2 Reliability of dynamic time-of-use response

The Low Carbon London program has trialled the use of a dynamic time-of-use (dToU) tariff to incentivise changes in load patterns of residential customers. dToU tariffs differ from time-of-use in that the schedule changes dynamically over durations of hours or days. This allows retail prices to react to changes within the electricity system and therefore more efficiently reflect the cost of generation and delivery of electricity. This trial looked at the potential value of the dToU tariff to the DNO, where it may be used for network Constraint Management (CM), displacing or deferring network reinforcement costs, and to the supplier, where Supply Following (SF) may contribute to system balancing. These use cases were examined in unison so that the potential conflicts and synergies between them may be observed.

This report builds on LCL report A3 [1] and proceeds to investigate in detail how the implementation of dToU tariffs may impact network reliability. Two main questions are addressed: first, the extent to which the DNO can count on dToU tariffs to reliably alleviate network constraints; second, how the use of dToU tariffs by suppliers may cause demand to violate network constraints.

### 2.1 Trial design

The details of the trial design and sampling procedure are described briefly below. More detail can be found in LCL reports A2, *Residential consumer attitudes to time-varying pricing* [3]; and A3, *Residential consumer responsiveness to time-varying pricing* [2].

#### 2.1.1 Trial groups and sampling

Two trial groups were formed, one to receive the experimental dToU tariff, the other to act as a reference point for consumption on a standard flat-rate tariff, which we call the nonToU group. Programme partner EDF Energy conducted opt-in recruitment onto the trial from its pre-existing customers within the UK Power Networks' LPN distribution area (London area). A second, within-trial, round of opt-in recruitment was then used to populate the dToU tariff group. Throughout the recruitment process, CACI Acorn data [4] was used to guide recruitment and ensure that both trial groups had socio-economic class ratios similar to that of London.

During the trial, half hourly mean demand measurements (kW) were recorded for each household via their smart meters.

#### 2.1.2 Tariff description

In the LCL dToU trial, a day was considered to begin and end at 5am (local time), in line with the general circadian cycle. Consumers were notified in the morning at 08:00 on the day before delivery via the mobile phone network's short messaging service (SMS). Messages were delivered to in-home displays and mobile phones, if requested. The tariff utilised three price bands at 3.99, 11.76 and 67.2 pence per kWh; these will henceforth be referred to as the *low*, *default* and *high* price.

**Constraint Management (CM) events** were designed to reduce demand at the typical peak load times of the day. Elexon's load Profile Class 1 archetype was used to identify the times of peak load occurrence during the year. As such, CM events typically cover late autumn, winter and early spring seasons, and occur during weekday mornings and evenings, Sunday afternoons and Saturday evenings. In order to stimulate the maximum possible demand reduction, the peak reducing high price signal was sandwiched one either side by low price periods for the remainder of the respective trial day (which

begins at 5am). CM events were scheduled to cover one, two and three consecutive days. 13 CM events were scheduled during the trial, which, when disaggregating consecutive event days, covered 21 separate event days.

**Supply Following (SF) events** were designed to inform the potential use of dToU for supply balancing and, as such, were designed to provide data on the availability of DR at different times of day, seasons of year, and for a range of durations. Event durations of 3, 6, 12 and 24 hours were used for both high and low prices, uniformly subtending the day via staggered start times. Each unique event; defined by price, start-time and duration; was repeated 3 times during the trial year. Events were placed throughout the year in a randomised-block design [5] such that noise from time-of-day would cancel upon analysis.

Figure 2 shows a graphical representation of the unique price events in the dToU tariff, where uniqueness is defined by start-time and duration.

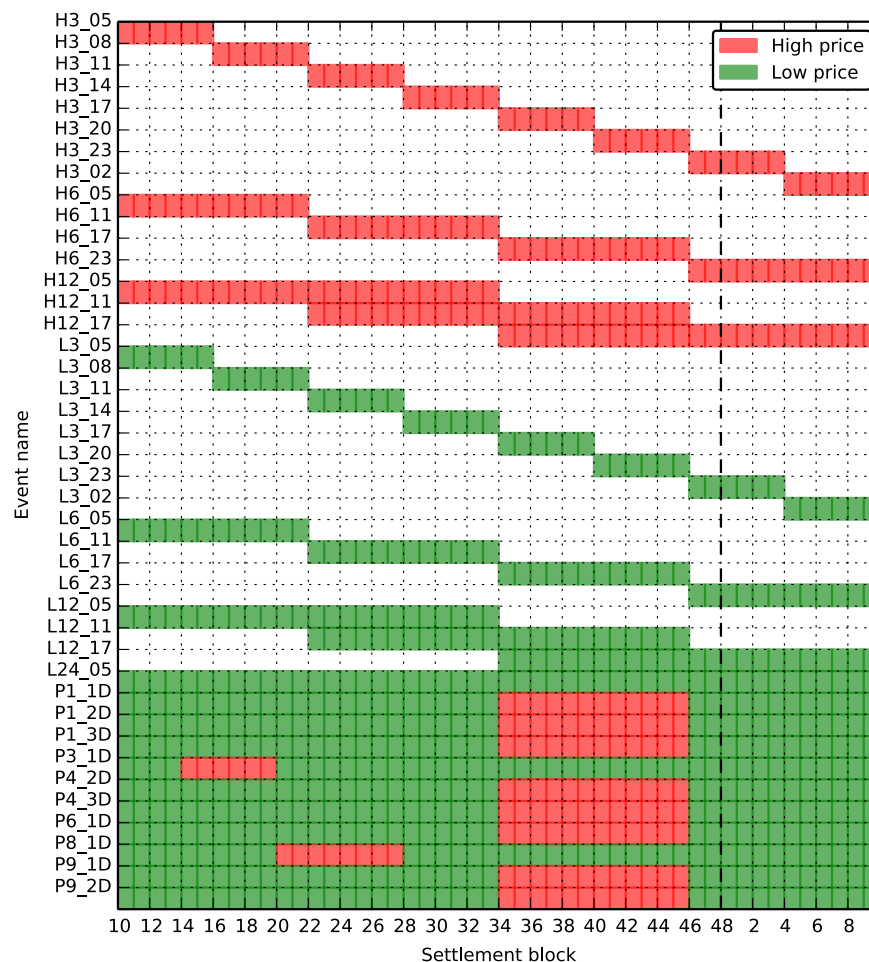


Figure 2: Pictographic representation of the unique price events in the LCL dToU tariff. ‘H’ and ‘L’ prefixes are used for SF events, ‘P’ for CM events. Half-hour settlement blocks are arranged in the order in which they occur in the trial day. Details of the CM events (‘P’ prefixed) can be found in Table 1.

## 2.2 Predictability of constraint management event response

The first question that is addressed is how a DNO can use dToU tariffs to alleviate network constraints. This analysis makes use of the constraint management (CM) trials, which specifically targeted load peaks. This section is concerned with quantifying the magnitude and variability of the observed

demand response for these events. It begins with the introduction of the baseline model that is used to calculate the mean DR values. The distribution of the CM events throughout the year is discussed, and correlations with baseline demand and weather variables examined. A simple model for CM event response magnitude is proposed. Confidence intervals for both this model, and for the response of the dToU group to a future event, are calculated.

### 2.2.1 A per-household baseline demand model

Demand response, in the context of this trial, is a reduction in demand relative to what would have been consumed without the price intervention, where price interventions are considered to be deviations from the default price. Quantification of demand response thus requires the establishment of a hypothetical baseline demand of the dToU group in the absence of the price event. A linear model was used to establish a baseline demand profile for each household in the dToU group. While the details of its implementation are more thoroughly described in report A3 [1], the salient points are described in the next section.

A key feature of this model is that it relates a household's baseline power consumption to the mean power consumption of the non-dToU group. This approach guarantees that the model captures events that could cause an overall bias – such as bank holidays, extreme weather and sports events – because they are expected to affect the dToU and non-dToU groups equally.

The predictor variables include the mean demand of the nonToU group and binary variables to allow for some time dependent structure. The final model takes the following form:

$$B_{h,m} = \alpha_h A'_m + \sum_{w=1}^W \beta_{w,h} T_{w,m} + \gamma_h m + \delta_h$$

where  $B_{h,m}$  is the predicted baseline demand of the dToU household  $h$  for the 30-minute measurement block indicated by measurement index  $m$ ;  $A'_m$  is the mean demand of the nonToU group for measurement  $m$ ;  $T_w$  is the dummy variable corresponding to hour-of-week  $w$ , 1 if the hour-of-the-week at time  $t$  is equal to  $w$ , 0 otherwise;  $W (= 168)$  is the total number of hours in a week. The index  $m$ , in conjunction with parameter  $\gamma_h$ , is also used as a linear growth term. Greek letters  $\alpha_h, \{\beta_{1,h}, \dots, \beta_{W,h}\}, \gamma_h$  and  $\delta_h$  are unknown parameters that were determined by the linear regression solver [6]. The model was trained using measurements from July-December 2012 and all non-event days in 2013 (the trial period). After cross-validation the model with random data slices, the mean R2 value was found to be 0.99. A more thorough description of the data and model validation can be found in report A3 [1].

This model was used to calculate a baseline mean demand for each household in the dToU group. Demand response was calculated as:

$$R_{h,m} = A_{h,m} - B_{h,m}$$

where  $R_{h,m}$  is the inferred demand response for household  $h$  at measurement  $m$ ;  $A_{h,m}$  and  $B_{h,m}$  being the actual measured demand and the calculated baseline of household  $h$  respectively. Note that the baseline model outlined above describes the *average* expected consumption of a household on a given day and hour. In contrast to baseline models that are used for demand response contracts [8], it does not attempt to predict random fluctuation in the household's power consumption, including the occasional absence of the inhabitants. As a result, the demand response estimates have an intrinsic variability related to the natural variability (diversity) of demand. It can be argued that this approach is

most applicable to the constraint management context where a DNO must take a decision on the basis of a load forecast. The baseline model may be considered an approximation of an optimal day-ahead load forecast.

### 2.2.2 High price demand response by CM event

This section quantifies the observed demand response during the high price period of each event. The duration of the high periods, and therefore the number of half-hour measurements taken, depends on the peak that was targeted (defined by time of day and day of week). For example, in the case of weekday evening peaks, this was 6 hours, from 17:00 to 23:00. Some CM events targeted peaks on consecutive days, and the results for each day are treated as independent observations. We aggregate the measurements into single value measure of DR for each CM event day: mean power reduction over the high price period, calculated as:

$$R_{event} = \sum_{h=1}^N \sum_{m=a}^{a+M-1} \frac{R_{h,m}}{NM}$$

Here  $R_{event}$  is the mean for the CM event day,  $N$  is the total number of households in the dToU group,  $a$  is the measurement index of the first high price period of the CM event;  $M$  is the total number of measurements in the high price period; and  $R_{h,m}$  is the DR measurement (as defined in Section 2.2.1). While  $N$  is often the full dToU group complement of 922, sometimes, due to data dropouts, this may be fewer by a small number. For each of the 21 event days we obtain one mean DR observation,  $R_{event,h}$ , from each household in the dToU group.

It is reasonable to assume significant independence and absence of bias of the errors in the inferred demand response values for each household. Random fluctuations in the nonToU response that affect all baselines are assumed to be small, because of the large number of households in the nonToU group. As the per-event DR measurements are themselves the mean of the DR estimates from all households in the dToU group, the central limit theorem applies and the standard error of the mean is used to estimate the measurement error. The results of this process and the times of the CM events are plotted in Figure 3; the numerical values are given in Table 1.

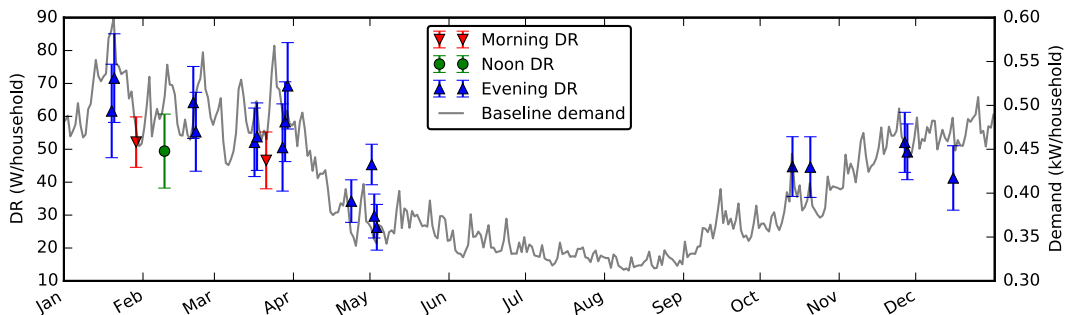


Figure 3: Mean DR for each CM event at high price where DR error bars indicate the standard error of the mean measurement. Baseline demand is calculated as the mean demand of each trial day.

It can be seen in Figure 3 that the CM event DR reduces towards the summer months. As residential demand during summer is significantly less than during winter, this suggests that either weather or the baseline demand may be influencing factors on response magnitude. Furthermore, one may expect dToU demand response to change over time as people gain experience with the programme, resulting in either decreasing (novelty wearing off) or increasing trends. To investigate these relations further, we

examine the DR correlation with the baseline demand level, three readily available macroscopic weather measurements; temperature, wind speed and solar elevation angle; and the numerical event index. In the case of solar elevation, 0° is considered to be the when the sun is at the horizon, and 90° when the sun is directly overhead.

**Table 1: CM events and mean DR and standard error on the mean for the high price period of each CM event day.**

| Event index | Event name | From (GMT)     | To (GMT)       | Duration (hours) | DR mean (W) | DR standard error (W) |
|-------------|------------|----------------|----------------|------------------|-------------|-----------------------|
| 1           | P9_2D      | 19/01/13 17:30 | 19/01/13 23:00 | 6                | 62          | 14                    |
| 2           | P9_2D      | 20/01/13 17:30 | 20/01/13 23:00 | 6                | 72          | 13                    |
| 3           | P3_1D      | 29/01/13 07:30 | 29/01/13 10:00 | 3                | 52          | 8                     |
| 4           | P8_1D      | 09/02/13 10:30 | 09/02/13 14:00 | 4                | 49          | 11                    |
| 5           | P4_2D      | 20/02/13 17:30 | 20/02/13 23:00 | 6                | 64          | 11                    |
| 6           | P4_2D      | 21/02/13 17:30 | 21/02/13 23:00 | 6                | 55          | 12                    |
| 7           | P9_2D      | 16/03/13 17:30 | 16/03/13 23:00 | 6                | 52          | 10                    |
| 8           | P9_2D      | 17/03/13 17:30 | 17/03/13 23:00 | 6                | 54          | 10                    |
| 9           | P3_1D      | 21/03/13 07:30 | 21/03/13 10:00 | 3                | 47          | 9                     |
| 10          | P4_3D      | 27/03/13 17:30 | 27/03/13 23:00 | 6                | 50          | 13                    |
| 11          | P4_3D      | 28/03/13 17:30 | 28/03/13 23:00 | 6                | 58          | 12                    |
| 12          | P4_3D      | 29/03/13 17:30 | 29/03/13 23:00 | 6                | 69          | 13                    |
| 13          | P1_1D      | 23/04/13 16:30 | 23/04/13 22:00 | 6                | 34          | 6                     |
| 14          | P1_3D      | 01/05/13 16:30 | 01/05/13 22:00 | 6                | 45          | 6                     |
| 15          | P1_3D      | 02/05/13 16:30 | 02/05/13 22:00 | 6                | 30          | 7                     |
| 16          | P1_3D      | 03/05/13 16:30 | 03/05/13 22:00 | 6                | 26          | 7                     |
| 17          | P6_1D      | 13/10/13 16:30 | 13/10/13 22:00 | 6                | 45          | 9                     |
| 18          | P6_1D      | 20/10/13 16:30 | 20/10/13 22:00 | 6                | 45          | 9                     |
| 19          | P1_2D      | 26/11/13 17:30 | 26/11/13 23:00 | 6                | 52          | 9                     |
| 20          | P1_2D      | 27/11/13 17:30 | 27/11/13 23:00 | 6                | 49          | 8                     |
| 21          | P9_1D      | 15/12/13 17:30 | 15/12/13 23:00 | 6                | 41          | 10                    |

The top row of Figure 4 shows the five listed variables plotted against the demand reductions of the CM events. As measurement errors were estimated independently, weighted least square regression was used to select the best-fit line through the data. The sample weights were set to  $1/\epsilon_i^2$ , the best linear unbiased estimator, where  $\epsilon_i$  is the standard error of measurement  $i$ . The remaining rows show dependencies between pairs of possible explanatory variables; the lines were fitted using ordinary (unweighted) least squares. The p-value for the gradient parameter is shown above each plot. This indicates the computed probability of the null hypothesis that the non-zero value of the fitted parameter was observed as a result of random noise.

It can be seen in Figure 4 that temperature, baseline demand and chronological event index show significant correlation with the DR magnitude while both solar angle and wind speed show poor correlations. Given the low and almost equal p-values for both baseline and temperature, we might conclude that they are both equally good predictors of response magnitude. Indeed, temperature and baseline demand are also highly correlated with each other. This is not surprising, as temperature is known to be a strong predictor of household demand – most demand forecasting algorithms utilise temperature as an input.

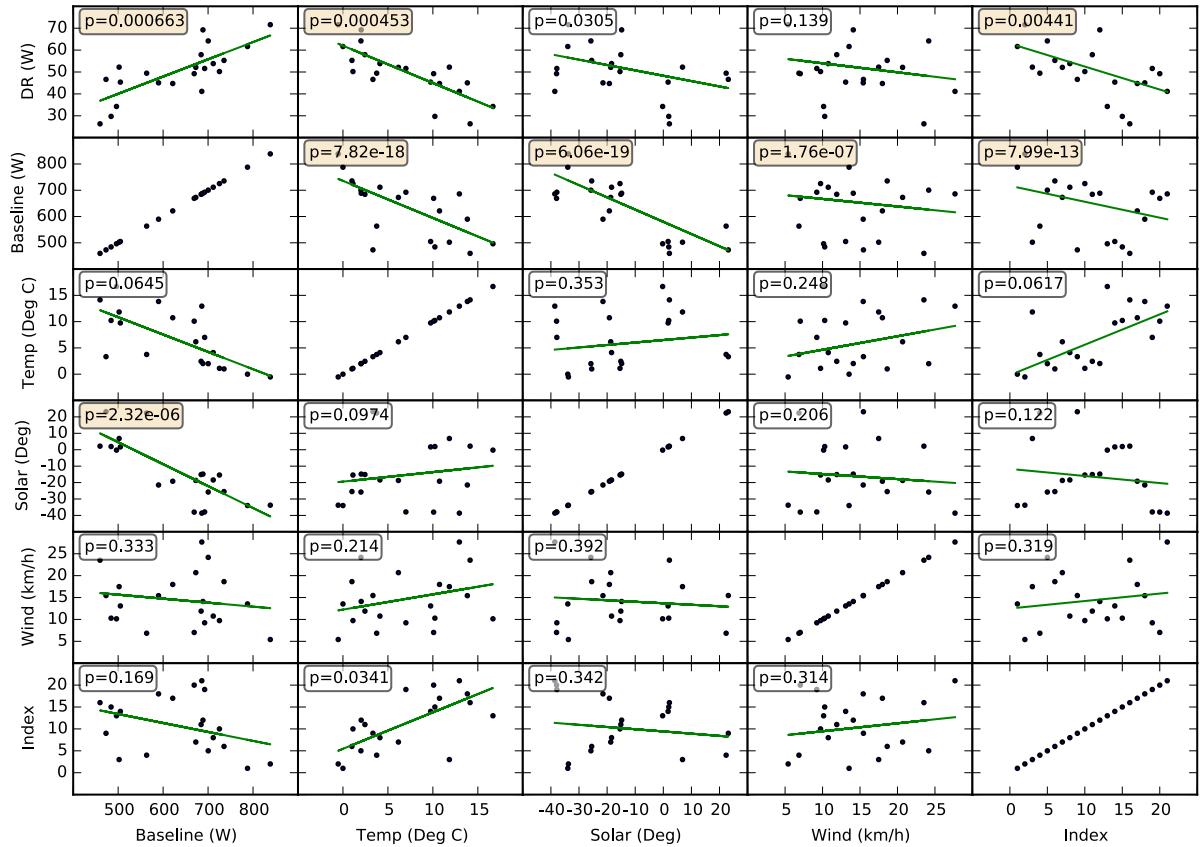


Figure 4: Best fit trend lines for CM event demand response during the high price period. Trends are examined for potential predictor variables: baseline demand, mean temperature, solar elevation angle, wind speed and chronological event index. Indicated p-values are for the gradient parameters only. Those lower than 0.01 are highlighted as being potentially significant. Temperature and wind data from [9], solar data from [10].

The significance of the order index indicates that there may have been some reduction in response as the trial progressed. However, that the index also shows a significant relationship with baseline demand, and perhaps also with temperature, suggests that the ordering of the events may have coincidentally correlated with variables that are indicators of demand response.

### 2.2.3 A response model for CM events

We proceeded to identify models for the observed responses to CM events. We considered the class of all linear models with a single explanatory variable, either with or without intercept (a constant term). The weighted least squares method was used to fit the linear models to the data using specified standard errors for the individual observations. Fitting was performed using the *Mathematica* software [7]. Suitability of the resulting models was evaluated according to the following criteria:

- Goodness of fit: preference was given to models that provided a good fit to the data. This was evaluated using the fraction of sum-of-squares of demand response values that was explained by the model. This is similar to the *coefficient of determination* ( $R^2$ ), though it does not discount the constant (mean response) contribution of the model.
- Significance of included terms: p-values were computed for the significance of each of the parameters, quantifying the probability that a non-zero value was obtained by chance. The p-values thus indicate whether the model provides a significantly better fit with the related term than without it. P-values of 0.01 for all parameters, including the constant offset, were required to be classified as a significant model, in order to avoid overfitting.

- Compatibility of residuals with input errors: the standard error estimates for the individual events provide an *independent* estimate of the quality of fit that is obtained. For each linear model, standardised residuals were computed. For an accurate model, these residuals should follow a standard normal distribution with mean 0 and variance of 1. The Anderson Darling test was used to compute a p-value for the compatibility of the observed residuals with the standard normal distribution. Its value should not be close to 0.

We emphasise that this procedure identifies *empirical* models that provide a sufficient description of the features present in the data. Although they might suggest an underlying mechanism for demand response, these models are not postulated with reference to the causes of demand response. The ‘true’ population models are almost certainly more complex than the models identified in this manner, but the number of CM events and the accuracy of the associated measurements limits the ability to identify such dependencies.

Two simple models were selected according to the criteria described above:

$$R_{CM}^{demand} = 0.078 \times [\text{baseline demand}] + (\text{random variation})$$

$$R_{CM}^{temp} = 60.8 - 1.71 \times [\text{temperature in } ^\circ\text{C}] + (\text{random variation})$$

The demand-model  $R_{CM}^{demand}$  can be interpreted as an ability to reduce demand by approximately 8% with respect to the baseline. This simple model accounts for 98.0% of the sum-of-square DR values, the parameter has a p-value of  $5.1 \times 10^{-16}$  and the Anderson Darling test for the standardised residuals compared to a standard normal distribution results in a p-value of 0.90 [7]. The alternative temperature-based model  $R_{CM}^{temp}$  suggests an ability to reduce demand that decreases with temperature. This model accounts for 98.2% of the sum-of-square DR values, the maximum p-value of its parameters is 0.0004, and the Anderson Darling test for the standardised residuals results in a p-value of 0.45 [7].

Clearly, both models are consistent with the data. Furthermore, the ability to use either baseline demand or temperature as a dependent variable is rooted in the correlation of baseline load and temperature (see Figure 4). We note that the use of other *single* predictors, such as the event index (trial progress) resulted in less accurate models, but that does not imply these factors do not affect demand response. The negative correlation between demand response and the event index in Figure 4 suggests a reduction in responsiveness over time, but the evidence from the trial is not sufficient to disentangle this from other temporal effects, such as the dominant temperature changes.

Figure 5 shows the measured demand response values plotted against the baseline demand (top) and average outside temperature during the high-price period (bottom). Standard errors are indicated using vertical lines. The dark green bands indicate 95% mean prediction intervals for the simple DR models  $R_{CM}^{demand}$  and  $R_{CM}^{temp}$ , derived from confidence intervals on their parameters. These reflect the range of likely models given the observed data. For the demand-based model  $R_{CM}^{demand}$  (top), the 95% confidence interval corresponds to a load reduction of 7.1%-8.4% of baseline demand.



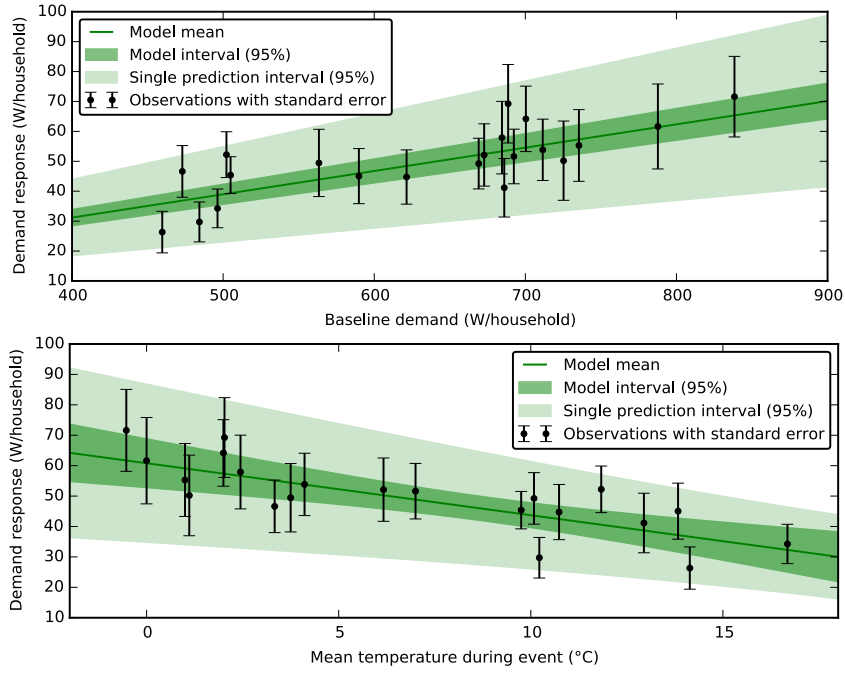


Figure 5: Observed demand response for CM events (black dots; standard errors indicated), alongside fitted empirical models. Demand-proportional (top) and temperature-linear (bottom) models are shown. Dark green bands indicate 95% mean prediction bands (range of models); light green bands indicate 95% single prediction intervals.

A question of considerable importance is how this model may be used to predict the magnitude of responses for future events. Note that at this stage we restrict ourselves to predicting future events of the same dToU population, i.e. a hypothetical continuation of the LCL trials. There are two distinct sources of uncertainty associated with future observations. The first contribution is the model uncertainty, represented by the darker green shaded areas (model mean) in Figure 5. In addition, there is a second contribution related to the households' realised performance compared to their respective baselines (analogous to a 'measurement error'). The two contributions are independent and both assumed to be normally distributed. The total variance is therefore equal to the sum of variances associated with each contribution:

$$\sigma_{prediction} = \sqrt{\sigma_{model}^2 + \sigma_{sampling}^2}$$

For each of the linear DR models, a model of the same type was fitted to the measured standard errors, resulting in linear noise models  $\sigma_{sampling}^{demand}(demand)$  and  $\sigma_{sampling}^{temp}(temperature)$ . The noise is assumed to be normally distributed according to the fitted standard deviation and 95% confidence intervals for single event predictions were computed by combining both sources of variance. The resulting intervals are indicated by the lighter shaded areas (single prediction interval) in Figure 5. In the case of the proportional demand model, the prediction interval includes load reductions from 4.6% to 11.0%. The temperature-linear model results in fluctuations of similar magnitude, but with less compact expressions.

### 2.3 Contribution to network capacity

The analysis up to this point (Section 2.2 and previously in Report A3 [1]) has considered the demand response observed within the LCL trials and determined what information can be extracted regarding the behaviour of the households in the dToU group. In this section an attempt is made to extrapolate

these findings to future constraint management scenarios, where the DNO arranges for a high-price signal to be broadcast in order to alleviate network constraints.

In this section, the probabilistic contribution of residential DR to network capacity is defined, and its value is estimated from the LCL dToU trial data. The computed contributions are compared with the naïve estimate of the mean demand response. For this analysis we shall assume that the measured consumption levels of the dToU group are representative of those of the population as a whole, and that a sample of  $N$  households is a selected randomly from the dToU population. Computations will be performed on a per-event basis.

The selection of  $N$  random households from the dToU population is appropriate to illustrate the overall range of responses that may be encountered. Conceptually, this reflects a situation where the households are unknown. However, in a situation where dToU signals are regularly used for DNO constraint management, the DNO will be in a position to learn about the response of households connected to specific substations or feeders. This knowledge should then be used to constructed site-specific response profiles, which reduce the magnitude of uncertainty for future events.

### 2.3.1 Definition of capacity contribution

In probabilistic terms, the *required network capacity*  $C$  may be defined as the capacity that is needed in order to satisfy the expected maximum demand plus a safety margin to cover random load fluctuations with a stated level of confidence (i.e. after-diversity maximum demand). The *capacity contribution*  $R$  of demand response is then defined as the change in required network capacity that results from the use of the dToU signal:

$$R = C - C_{CM}$$

where  $C_{CM}$  is the required physical network capacity when the dToU signal is used. It is defined such that the probability of reaching the capacity constraint is kept constant with respect to the reference scenario without demand response. The value of  $C_{CM}$  is thus implicitly defined by

$$\Pr(D_{CM} \geq C_{CM}) = \Pr(D \geq C).$$

Here  $D$  is the total demand in the absence of a price event;  $D_{CM}$  is the total demand if there is a CM event.

For the purpose of this analysis, the total demand  $D$  is considered to be the sum of  $N$  randomly selected households. When  $N$  is sufficiently large, the central limit theorem applies (analysis not shown here), which allows us to describe the total (or mean) demand distribution of a group of households with the mean and standard deviation of the raw demand measurements. The dToU signal may affect both these distribution parameters. We have already seen, in Section 2.2.3, that the mean demand is typically reduced by 7% to 8% as a result of a CM event. In a plot of the probability density function (PDF) of total demand, the curve is shifted to the left by this amount. We will see that, in general, the CM event also reduces the variance, so that a narrower, more concentrated distribution will result.

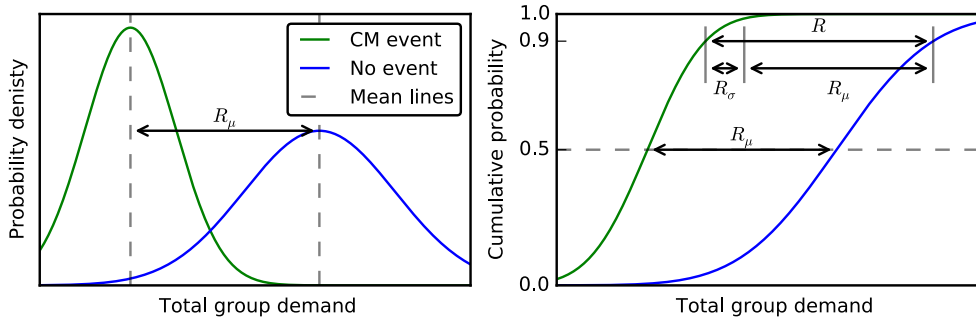


Figure 6: Illustrative probability density curves for demand during a CM event and, the counterfactual, what it would have been had there been no event.

These changes are illustrated in Figure 6 (left), where  $R_\mu$  indicates the difference in mean as a result of the CM event. For ease of annotating the graphic, let us imagine the normal capacity limit is enforced to a probability of 0.9. The network *capacity contribution* is therefore the difference between the cumulative probability functions (CDF) when both are equal to 0.9. This is illustrated in Figure 6 (right), where  $R$  indicates the total network capacity contribution of the CM event. We may think of the *capacity contribution* ( $R$ ) of DR as comprising two components: mean shift in demand, which we shall call the *mean response* ( $R_\mu$ ), and change in the confidence interval on this mean which we shall call the *variance response* ( $R_\sigma$ ):

$$R = R_\mu + R_\sigma$$

The variance response ( $R_\sigma = R - R_\mu$ ) is a result of a decreased dispersion of the group demand relative to the counterfactual no-event situation. This manifests as a steeper CDF curve, as illustrated in Figure 6 (right). Conversely, if the CM event had the opposite effect, increasing the variance of the demand distribution, then the variance response would detract from the capacity contribution of demand response.

The *mean response* ( $R_\mu$ ) is, in the context of this discussion, considered to be a fixed quantity. However, the *variance response* will be enhanced under the following conditions:

- If the number of households in the CM event is fewer: Because uncertainty in the magnitude of the group demand is proportional to  $1/\sqrt{N}$ , a reduction in uncertainty (decrease in variance) will have a proportionally greater effect at lower  $N$ . As  $N$  increases, the total capacity contribution ( $R$ ) tends towards the mean response ( $R_\mu$ ).
- If the certainty that the capacity limit will not be breached is made more stringent: It can be seen in Figure 6 (right) that the greater the certainty (cumulative probability) that the group demand will not exceed a certain limit, the greater the difference in demand between the *no-event* and *CM event* CDF curves.

### 2.3.2 A group baseline standard-deviation model

The analysis approach outlined in the previous section requires the *mean* and *standard deviation* of demand for the dToU group, both during the CM event, and for the hypothetical situation in which the CM event did not occur. A per-household baseline demand model was introduced in Section 2.2.1, and the mean of the household baselines establishes a baseline model for the mean. We now introduce a second baseline model to predict the *standard deviation* of the dToU group demand during the CM event.

The dToU and nonToU groups are drawn from similar but not identical populations. Therefore a basic linear model is proposed to predict the standard deviation of the dToU group  $S_m$  in terms of the nonToU group's mean demand ( $A'_m$ ) and its standard deviation ( $S'_m$ ) of demand:

$$S_m = \alpha A'_m + \beta S'_m + \gamma$$

Here  $m$  is the index of the 30-minute measurement block; Greek letters  $\alpha$ ,  $\beta$  and  $\gamma$  are unknown parameters that were determined by the linear regression solver [6]. The model was fitted on all available data for the dToU and nonToU groups for July-December 2012 and the non-event days of 2013. Cross validation showed the model to have a coefficient of determination ( $R^2$ ) of 0.94.

### 2.3.3 Effect on demand mean and standard deviation

Using the two baseline models, one for the dToU group demand *mean* and the other for its *standard deviation*, we may observe the effect of the CM event high price on these statistics. The difference between the actual and baseline is calculated for both the demand mean and standard deviation, for each CM event. The absolute reduction in each is depicted in the bar chart in Figure 7.

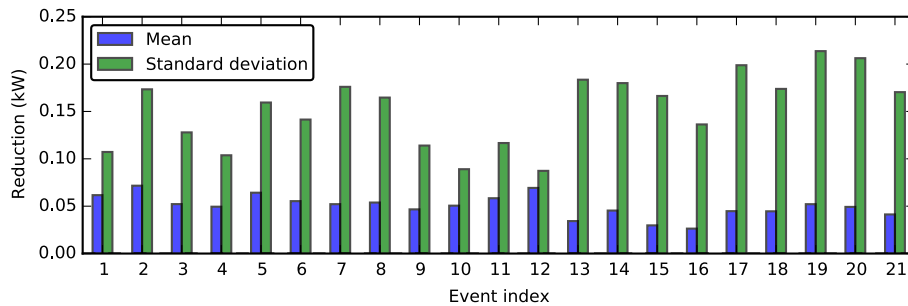


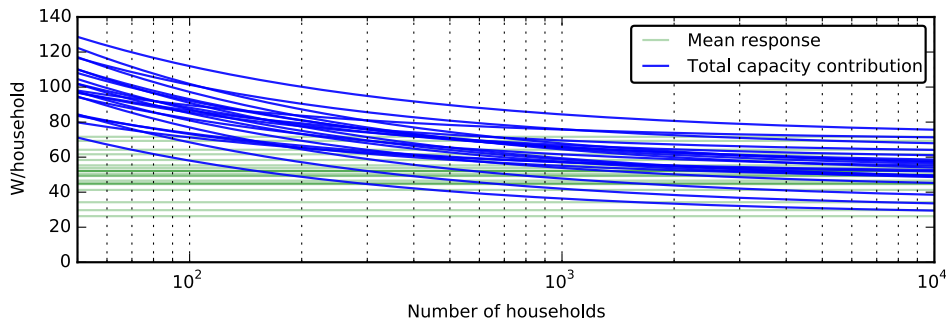
Figure 7: Reduction in demand mean and standard deviation as a result of the CM event.

While the reductions in the mean demand (which we call DR) have been discussed in detail, this figure shows that the CM events also have an impact on the standard deviation of demand. In all cases the CM event resulted in a reduced standard deviation of the households' consumption levels. From a network capacity perspective this results in a greater certainty regarding the prediction of future aggregate demand, which may be converted into an effective network capacity contribution using the approach explained in Section 2.3.1.

### 2.3.4 Mean capacity contribution by number of households

Using the analysis approach described in Section 2.3.1, we calculate the effective network capacity contribution per household, plotted against the number of households in the group. This is repeated for each CM event and shown in Figure 8. Note that these results represent the ensemble of all possible selections of  $N$  households (with duplicates) from the group of dToU observations. Analysis for specific

customer groups (e.g. those on a particular substation) should be performed using location-specific probability distributions.

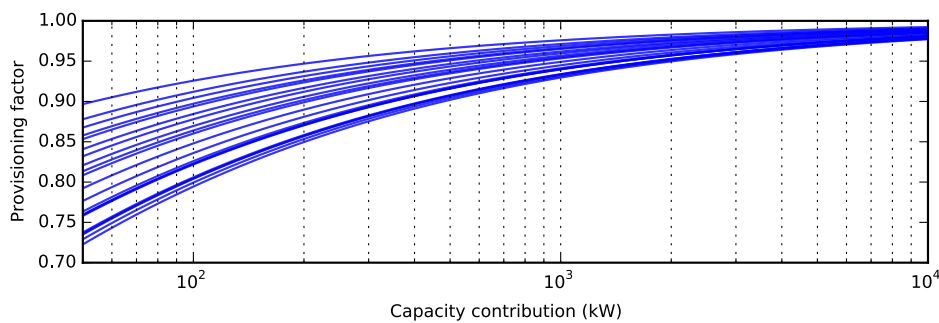


**Figure 8: Effective network capacity contribution per household against the number of households in the group, for each CM event (one line per event). The mean DR levels are plotted for reference.**

On the left of the graph, where the number of households equals 50, the network capacity contribution per household, depicted by the blue lines, substantially exceeds the mean contribution, at between 70 W and 130 W relative to a mean contribution of between 30 W and 70 W. Due to the rapid decline in capacity contribution with group size, a logarithmic scale is used for the number of households in order to increase clarity. For a group size of 1000 households, the capacity contribution is approaching the mean response contribution – the difference between the actual and baseline mean demand, depicted in green in the figure. When the group size reaches 10,000 households, little difference can be seen between the total network capacity contribution and the mean response.

### 2.3.5 Provisioning factor by desired network capacity contribution

By dividing the total mean response of  $N$  households by the total network capacity provided by  $N$  households, we create a ratio, which we call *provisioning factor*. This may be thought of as an indicator of the fractional change in the group size necessary to deliver a particular network capacity, as a result of the incorporation of *variance response* into our DR model. Figure 9 shows the provisioning factor plotted against the desired total network capacity for each of the CM events in the trial.



**Figure 9: Provisioning factor plotted against the desired total network capacity (aggregate mean response) for each of the CM event in the trial.**

The figure shows that the reduction in the necessary group size when variance response is considered can be significant when small network capacity contributions are required. For example, if a network capacity contribution of 50 kW was desired, the group size necessary to deliver this may be as much as 25% smaller than that which would be required if only mean response was considered. These savings are quickly lost as the desired capacity contribution is increased. Much past 1 MW, and the mean response alone is almost sufficient to describe the network capacity contribution per household. To

place these numbers in perspective, a capacity contribution of 50 kW corresponds to the mean CM contribution of approximately 1000 households, but the variance response reduces the number of required households to approx. 800 – equivalent to two or more distribution substations. A response on the order of 1 MW may be delivered by the customers connected to a primary substation (approx. 10,000-25,000 in domestic areas).

For smaller contributions there is considerable variation in the provisioning factors between each CM event, without a pronounced pattern. Data from a future large-scale rollout of dToU tariffs may be used to try to identify explanatory variables for these differences. Nevertheless, the LCL trial observations give confidence in the *sign* of the deviation: variance reduction results in a contribution that consistently outperforms the mean (provisioning factor less than one).

The maximum relative magnitude of the variance response is only about 25% for a DR event that involves 50 kW of capacity (aggregate mean response), dropping off to 10% for a 1 MW capacity. This may be compared to the uncertainty in response due to inter-event variation (discussed in Section 2.2). For the demand-proportional model, the prediction interval at 95% confidence was shown to be between a 4.6% and 11.0% demand reduction. Given an expectation value of 7.8%, the model prediction could vary more than 40% in either direction. We may therefore conclude that inter-event variation is by far the biggest contributor to uncertainty in residential DR and, in most cases, variance response may be ignored without material consequence.

## 2.4 The risk of low price signals to network operations

Up to this point, this chapter has been concerned with analysing the potential of dToU signals that aim to strategically alleviate network constraints on behalf of the DNO. This section regards the alternative and arguably more likely case where prices are set by the suppliers in accordance with day-ahead or real-time market conditions. For example, an excess of available wind energy may result in low prices being broadcast to consumers in order to incentivise demand shifting and so avoid wind curtailment. However, such an intervention may boost demand far above previously anticipated levels and thus pose a risk to network operations.

This section aims to quantify the extent to which demand may be boosted by low prices, using data from the LCL Supply Following dToU trials. The supply following (SF) events in this trial were designed to sweep through all times of day with a variety of durations of both high and low price events so as to create a general overview of people's willingness to trade flexibility for savings on their energy bill. These events were randomly distributed throughout the year in a randomised-block design. More details are given in Section 2.1.2.

The network capacity required to supply a collection of residential loads is determined by the largest credible peak in the aggregate load (after-diversity maximum demand). For this reason, the remainder of this section will focus on the analysis of peak load levels, comparing observed peak loads with predicted daily peak loads according to the baseline model. It is tempting to consider only annual load peaks (i.e. 'winter peak' scenarios), but this would ignore operational decisions that cause temporary capacity constraints. For example, maintenance work may be scheduled during summer months when the expected peak load levels are lower, or network flows may be rerouted after faults. We therefore consider the occasions when the peak load exceeds its normal level as potentially relevant to the DNO, because it may affect operational decisions.

### 2.4.1 Day peak compared to event peak

For each SF low price event in the trial, the settlement block with the highest mean consumption was identified (within the low price interval). This block was designated the *event peak*, and the corresponding consumption level was recorded. 95% confidence intervals were constructed using the standard errors estimated using the individual household measurements for each event peak.

For each *event peak*, the corresponding baseline demand peak of that day was determined by averaging the baseline demand over all households for each 30 minute settlement block and selecting the maximum value. This was designated the *day peak*. The 95% confidence intervals were constructed using the value of baseline standard deviation model (introduced in Section 2.3.2) at the time of the *day peak*.

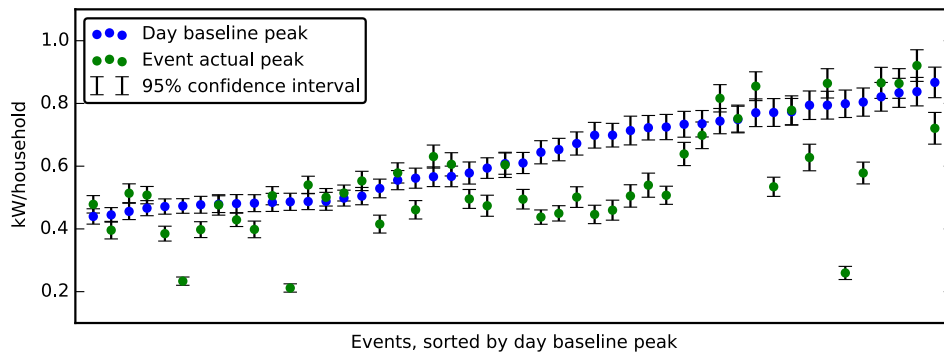


Figure 10: Day peak (blue) and event peak (green) demand with respective 95% confidence intervals (N = 922).

Figure 10 shows the values of the *event peak* and *day peak* demand for each low price event in the trial. Events are sorted in order of the magnitude of the day peak. While many of the low price events do not cause demand to exceed the expected peak of the day, it can be seen that a little more than half of the events observed lie close to or exceed the expected day peak.

The distribution of peak breaches shows no obvious sign of depending on the expected peak demand of the day. As the expected peak demand is highly dependent on season of year and day of week, this suggests that peak increases may be possible during all season and day types – an interpretation which is investigated further in the next section.

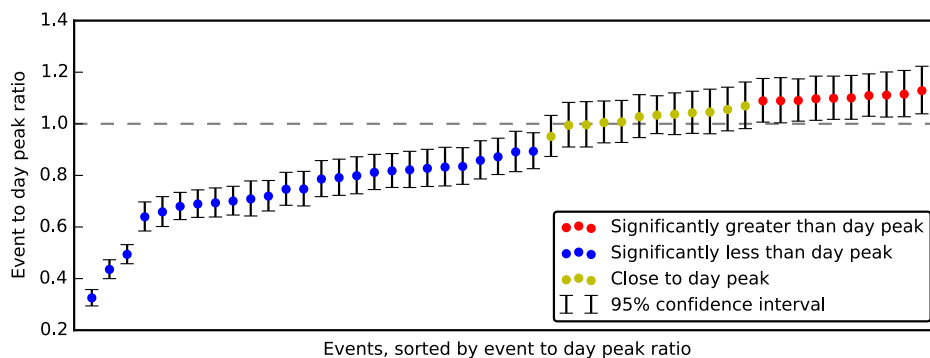


Figure 11: Event peak to day peak ratio with 95% confidence intervals (N = 922).

To more clearly observe the potential impact of low prices on daily peak loads, we plot the ratio of event peak to day peak consumption, shown sorted by this ratio in Figure 11. Due to the uncertainty in the distribution of the ratios (normality cannot be assumed here), 95% confidence intervals were constructed numerically. For each low price event this was computed as follows: The demand of the day



and event peaks were modelled as normally distributed random variables with parameters of the mean and standard error of their respective household demand measurements. The ratio of these random variables was sampled  $10^6$  times and the interval that contained 95% of the sorted values, centred about their mean, was used as the confidence interval.

Ten events (shown in red) resulted in peak load levels that significantly exceeded the baseline peak, and twelve further events (yellow) are not incompatible with an increase in peak load at the 95% confidence level. Furthermore, the measured peak load during the red events exceeded the baseline load by 10% on average. This suggests that the broadcast of low price signals may cause significant increases in peak load, in the order of 10% above the baseline peak level.

### 2.4.2 Relationship of peak increases with time of day

The lack of correlation between peak increases and the magnitude of the expected day peak (shown in Figure 10 and discussed in the previous section) indicates that peak-increasing events may occur across all seasons, and possibly days of the week. Here, the relationship with type of day (weekday, weekend) and time-of-day is investigated.

We compute the demand to day peak ratio for each actual demand measurement during the low price events. This provides a clearer and more complete overview than the analysis in Figure 11, which only selected the peak level. This approach uses the demand measurements taken during the low price events to form a visual map of the ratio of low price demand to the expected peak demand during the respective day.

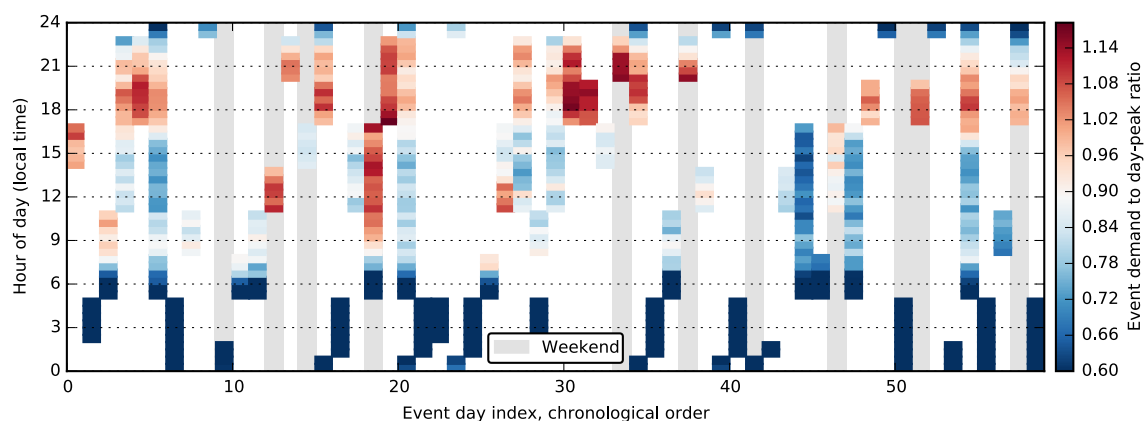


Figure 12: Map of the event-peak to day-peak ratio in chronological order, plotted against hour-of-day. Grey backgrounds indicate events that took place during the weekend.

Figure 12 shows the image created by the above process. The low price event days are listed along the x-axis in chronological order. For each demand measurement in each low price event, the ratio to day-peak demand is plotted at the corresponding time-of-day on the y-axis. The colour of the measurement point is used to indicate its value. Weekend events are indicated by grey shaded background. Because trial days begin and end at 5am, some events straddled two days. As such, the 48 low price SF events appear across 58 discrete days.

It is immediately evident that most of the peak increases occurred during weekday evenings or weekends. An exception to this trend was the event at index number 26, on 12 July 2013, where the demand on a Friday afternoon exceeded the anticipated daily peak. This event, which may be caused by summer holidays, suggests that care must be taken to anticipate peak load increases even on weekday

afternoons. Interestingly, weekday morning events were not observed to pose significant risk of peak increase. As was suggested in the previous section, there does not appear to be a seasonal trend. The low price events were spread, approximately evenly, throughout the year, and yet the same general pattern can be seen in all weekday and weekend events, respectively.

These findings should be viewed in the context of the trial. A number of factors have the potential to greatly change consumer's response to low price signals. Changes to the value of the low price signal, or to influencing factors such as the default or high price, may increase or decrease motivation to respond. Furthermore, increased penetration of home automation technology may enable households to respond at times that they currently find inconvenient, such as while they are out of the home or while they are sleeping.

## 2.5 Summary and discussion

This chapter has considered the effects of dynamic time of use tariffs on network constraint management. A statistical analysis of the Low Carbon London trial data was performed in order to quantify opportunities and risks from a reliability perspective.

First, the performance of the dToU trial group on the LCL constraint management trials was analysed with the aim to identify predictive models for the tariff-induced load reduction. Two linear models were identified that match the observed demand response values: a demand-proportional model and a model where the demand response depends linearly on temperature. The simplest model identifies the magnitude of demand response as 7.8% of the baseline demand during the peak period (95% confidence range: 7.1%-8.4%). In addition to this descriptive model, a predictive model was derived suggesting that future constraint management events for the same trial population would result in a demand reduction between 4.6% and 11.0% of baseline demand (95% confidence).

It should be noted that the two derived models are heuristic models that relate the observed demand response to the most descriptive observables. These do not necessarily imply a causal relation, and relevant factors may be omitted if they are not strictly necessary to explain the data with the observed accuracy. Data from future trials and commercial rollout of dynamic time of use tariffs will provide opportunities to refine these models.

The next step in the analysis was the extrapolation beyond the LCL trial setup, considering an arbitrary number of households of unknown composition. This reflects the situation where the DNO arranges for high-price signals to be broadcast to a set of households in order to alleviate network constraints. To quantify the extent to which demand response can alleviate network constraints, the *capacity contribution* of demand response was defined as the change in *required network capacity* that results from the use of the dToU signal. Here the required capacity is defined in probabilistic terms as the capacity that is needed in order to satisfy the expected maximum demand plus a safety margin to cover random load fluctuations to within a stated prediction interval (i.e. after-diversity maximum demand).

It was shown that the capacity contribution of demand response can be decomposed into two components: *mean response* and *variance response*. The variance response results from changes in the variance of consumption levels between households. In the case of the LCL constraint management trials, the high-price signal was always found to *reduce* the variance of household consumption levels, even more than suggested by the mean load reduction. This is consistent with trial participants opting to switch off or postpone the use of discretionary large loads, thus reducing the propensity of large load

peaks. The variance response thus has the effect of boosting the capacity contribution of demand response, as a lower capacity margin is required to anticipate peak load fluctuations.

To get an impression of the impact that the variance reduction effect has on the capacity contribution, its value was computed across a range of aggregation levels. Furthermore, the consumption distribution of the dToU trial group for each of the events was used as a set of hypothetical collective responses from which the households were sampled, effectively providing a sensitivity regarding response variability. In all cases, the variance contribution boosted the capacity contribution, but by an amount that decreases with the aggregation level. A boost of 25% compared to the mean response was observed at a mean demand response capacity contribution of 50 kW, decreasing to 10% at 1 MW and 5% at 10 MW. These are significant figures, but they are outweighed by the observed variability in the mean response itself, with fluctuations of 40% or more around the expected value. Therefore, in most cases, the additional contribution of variance response may be ignored without material consequence.

Finally, the focus shifted to potential conflicts between the DNO's local network management aims and the supplier's incentive to respond to wholesale electricity markets. At times of abundant wind power availability, the suppliers may broadcast low prices to consumers in order to incentivise demand shifting. However, the resulting additional demand may boost local demand far above previously anticipated levels and thus interfere with network operations.

The extent to which demand may be boosted by low prices was analysed using data from the LCL Supply Following dToU trials. It was confirmed that there is a considerable risk of increasing the load on distribution networks, with 22 out of 48 low price events achieving maximum loads that are consistent with or higher than the daily peak load, and 10 of those showing load levels that are significantly higher than the baseline (95% confidence). The enhanced load peaks all occurred on weekday evenings and weekend afternoons, but their occurrence does not appear to depend on the magnitude of the expected peak demand of the day. We note that these findings must be taken in the context of the trial: changes to the price signals may increase or reduce motivation to respond, while increased penetration of home automation may make it easier for consumer to respond at hitherto inconvenient times (e.g. sleeping or working hours).

## 3 Reliability of demand side response by industrial and commercial customers

Demand Side Response (DSR) by industrial and commercial customers comes in many forms, from back-up generators to intelligent control of office HVAC systems. Industrial & commercial (I&C) DSR is commonly being used to support the national generation infrastructure, usually mediated by aggregators. As part of the Low Carbon London program, UKPN has trialled the use of I&C DSR for the targeted alleviation of constraints in the distribution network. This chapter summarises the results of those trials and presents a detailed analysis for their implications for dependability of I&C DSR in this use case.

### 3.1 Trials and methodology

This section contains a brief overview of the LCL I&C trials and trial participants. This is followed by description of steps undertaken in data selection and analysis. Finally, the metrics of interest to this study are established and discussed. The scope of the description is restricted to the quantitative reliability analysis in this report. Where appropriate, references are included to more general discussions in LCL report A7 [11] and other literature.

#### 3.1.1 Summary of trials performed

Low Carbon London (LCL) I&C trials were designed and carried out in a similar manner to business-as-usual Demand-Side Response (DSR) Programmes exercised by various US utilities [13] and the GB Transmission System Operator [14].

Trial participants were recruited by the LCL aggregator partners with the aim to cover a diverse set of participant types. All participants were profiled by the aggregator, and their ability to reduce net load on the distribution network was established. Based on this analysis and the required DSR event duration, a committed load reduction capacity was determined and contractually agreed. Aggregators arranged participants into portfolios and submitted these portfolios to the DNO as the assets of fixed available capacity.

The next actions followed:

- a) On the day of a DSR event the DNO would send a signal to load aggregator(s), requesting a dispatch of one or more assets starting at a given time (e.g. 1 pm) and for a given duration;
- b) For chosen customers a load aggregator (or the DNO) would then construct customer baseline for that day using asymmetric High 5 of 10 baselining methodology [8][11] based on historical data;
- c) On the day of DSR event a load aggregator would send a signal to chosen trial participants in advance to time X (from 2-3 to 30 minutes in LCL trials, depending on participants' category), thus notifying them that they were required to participate in accordance with their contracts;
- d) After notification baseline adjustment was carried out [8][11];
- e) When DSR event was over, load aggregator (or the DNO) compared participant's performance to their baseline and rated the level of participant's success in accordance with established practice.

### 3.1.2 Trial participants and sample size

I&C trials were conducted as a part of the LCL programme in two batches. The first batch was realised in summer 2013 (from June to August) with a total of 128 DSR events generated by 26 participants. The second batch was conducted in winter 2013/14 (from December to February) with total of 61 response event obtained across 9 participants, 7 of which also participated in the summer trials. As a result, a total of 189 DSR events were scheduled for 28 sites in the course of two stages of trials.

The trial participants covered a broad spectrum of implementations. At a high level, these could be described by two categories, each with two sub-categories:

- a) Generation-led DSR, able to start generating on demand
  - a. on-site diesel generators
  - b. CHP engines with a cyclic operating regime
- b) Demand-led DSR, reducing site electricity consumption on demand
  - a. HVAC installations
  - b. Water pumping stations

Table 2 shows a breakdown of sample size of all 189 DSR events by season (summer/winter), category (generation-led DSR/demand-led DSR) and type of equipment used. For a detailed description of DSR event participants by month and time of day the reader is referred to LCL report A7 [11].

Table 2 Event counts per event class. Number of sites indicated in brackets.

| Trial time         |                            | Summer 2013 | Winter 2013/2014 |
|--------------------|----------------------------|-------------|------------------|
| Generation-led DSR | Diesel generators (5)      | 25          | 21               |
|                    | CHP plant (3)              | 11          | 9                |
| Demand-led DSR     | HVAC (15)                  | 62          | 31               |
|                    | Water pumping stations (5) | 30          | -                |
| Total events       |                            | 128         | 61               |

### 3.1.3 Data selection and preparation for analysis

#### Raw data collection and initial selection

On completion of the trials raw data was provided to the LCL Learning Lab in the form of load profiles for each of the 28 participating sites, covering both summer and winter trials. At this stage 2 sites (10 DSR events in total) were excluded from further analysis, as their load profiles were available only in half hourly resolution, which is insufficient to characterize 1-hour DSR events. The rest of provided profiles had 1-minute resolution. Five additional events (two in summer and three in winter trials) were excluded based on the fact that load profiles for those days were absent from data provided. In addition, one of the water pumping stations was excluded due to the non-responsiveness across all six relevant events. Finally, one CHP unit (13 events) was excluded from further analysis because of an apparent variable measurement offset that introduced spikes in measurements and baselines. The remaining 155 DSR events were taken to the next step: baseline construction.

#### Baseline construction

The demand side response (DSR) of a given site and event cannot be measured directly. Rather, it must be inferred from the measured electricity consumption and the load *baseline*, an estimate of what trial

participant's electricity consumption might have been in the absence of the DSR event [8]. The baseline takes the form of a reconstructed hypothetical load profile on the day of DSR event and it is used as a benchmark to quantify a participant's performance. In contrast to the work in Section 2 on the residential time-of-use tariff trials, there is no ready 'control' group with which to compare responses. This places greater emphasis on calculating site-by-site baselines from observations of a single site.

The meaning and importance of baselines along with advantages and disadvantages of various baselining methodologies were discussed at length both in report A7 [11] and a variety of publications [8] [15]. This report adopts the High 5 of 10 method with symmetric baseline adjustment, for the following considerations:

- a) High 5 of 10 is a good compromise between accuracy, simplicity and integrity [8] [15];
- b) This method (and its High X of Y variations) is widely used in DSR programmes [8];
- c) The aggregators in the LCL I&C trials estimated customers' performance using asymmetric High 5 of 10 baselines. It is less likely to 'punish' customers for accidental fluctuations and therefore a good fit for contractual purposes, but it suffers in accuracy compared to the symmetric High 5 of 10 baseline [8];

The Symmetric High 5 of 10 (H5o10) method constructs baselines using the following steps:

1. 10 working days prior to the DSR event day (i.e. excluding weekends, holidays and also previous event days) were selected;
2. Total electricity consumption (kWh) for each day was calculated, and 5 days with highest values were chosen;
3. Load profiles for these 5 days were averaged to produce the unadjusted baseline;
4. On the day of the DSR event a baseline adjustment was carried out by calculating average electricity consumption during the two-hour period prior to the notification both for trial participant's load profile and unadjusted baseline constructed on the previous step. Then these two values were compared and, if site's electricity consumption was larger than that of a baseline, then baseline was shifted up (by difference between the two values), and, if smaller, then baseline was shifted down respectively.

The high 5 of 10 method requires the availability of consumption measurements on 10 working days before the event. In order to enlarge the pool of available events for the probabilistic analysis, we opted to relax these strict requirements in two ways. When insufficient suitable days were available before the event, additional days were selected *after* the event date. Furthermore, when that was also insufficient, high 5-of-9 or high 4-of-8 were used as required.

This way, baselines were constructed for 153 events. For the two remaining events, load profiles for non-event days were not available, precluding the construction of a baseline. One additional event was discarded due to data dropouts on days used for constructing the baseline. The breakdown of DSR events ultimately accepted for analysis in this chapter is given in Table 3:

Table 3 Events accepted for further analysis

| Trial time         |                            | Summer 2013 | Winter 2013/2014 |
|--------------------|----------------------------|-------------|------------------|
| Generation-led DSR | Diesel generators (5)      | 23          | 18               |
|                    | CHP plant (2)              | 3           | 3                |
| Demand-led DSR     | HVAC (13)                  | 50          | 31               |
|                    | Water pumping stations (4) | 24          | -                |
| <b>Total</b>       |                            | <b>100</b>  | <b>52</b>        |

### *Estimation of trial participants' performance*

This report considers the dependability of I&C DSR as a tool for targeted load reduction by the DNO. In line with this aim we analyse the load reduction achieved by the trial participants, whereas the primary focus in LCL report A7 [11] was on contract compliance.

The trial participants varied significantly in the scales of their electricity consumption and response magnitudes. Furthermore, events of different duration occurred. In line with our aim to establish a quantitatively supported qualitative analysis of I&C response, all events were normalised to a common scale, both in magnitude and duration. This established two common scales (one for response level and one for event duration) on which participants' performance could be compared, aggregated, averaged or be subjected to other mathematical operations, depending on analysis purposes. The measured response (actual minus baseline consumption, in kW) was divided by the contracted response size to express the response in contracted units. Similarly, all events were scaled to an interval from 0 to 1, where 0 was scheduled response start and 1 the scheduled response end.

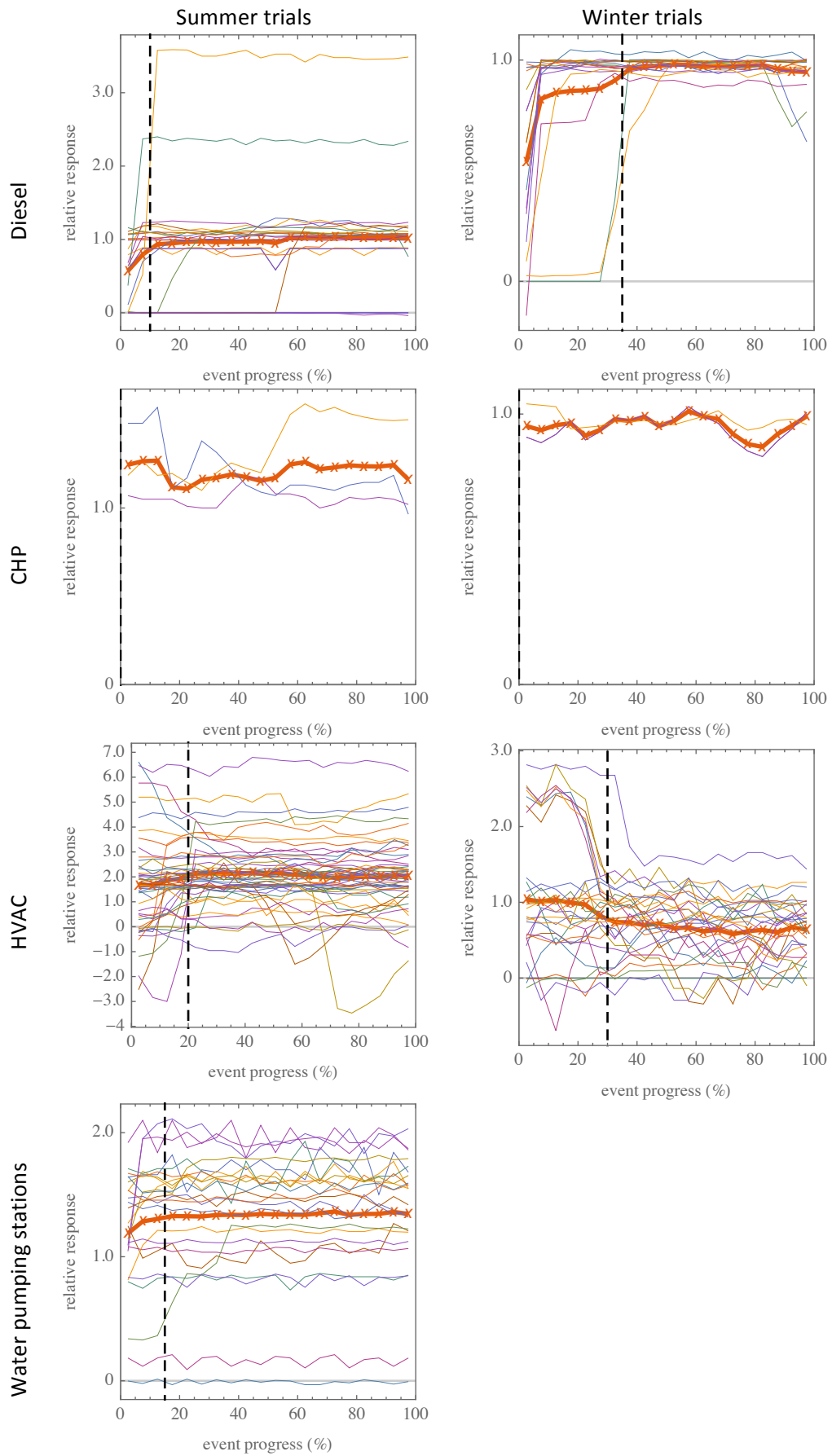
Figure 13 shows the resulting traces for all events, categorised by DSR technology and summer/winter trials. Traces were discretised into 20 intervals each by local averaging. This provides a level of smoothing that aids visualisation and also reflects the fact that fluctuations on very short time scales do not necessarily constrain the network, due to the thermal mass of network assets. A few general observations can be made based on these traces.

- Generation-led DSR (diesel and CHP) provides response values that are closest to the contracted amount, consistent with their direct controllability. The clear exception is when units did not respond at all, which happened four times for the diesel sites during the summer trials.
- The response of demand-led DSR (HVAC and water pumping stations) is more variable, both in terms of average magnitude and the inter-event variation. The inter-event variation may be partially attributed to fact that – in contrast to generation-led response – demand-led DSR is defined with respect to a non-zero, and therefore noisy, demand baseline.
- HVAC systems demonstrated much larger response magnitudes – and variability – in the summer trials than in the winter trials. This is consistent with the larger dependence on air conditioning in the summer months, allowing for larger reductions.

In addition to the above, initial transient behaviour was observed for many traces. This was often in the form of a late start of the response, but the HVAC winter trials also contained initial overshoots, where sites overdelivered before returning to a nominal power reduction level. After this initial ramp, most event traces demonstrate a relatively stable response. The vertical lines in Figure 13 indicate the visually identified transition between these two regimes for each DSR type and trial set.



Figure 13 Event traces used for statistical analysis

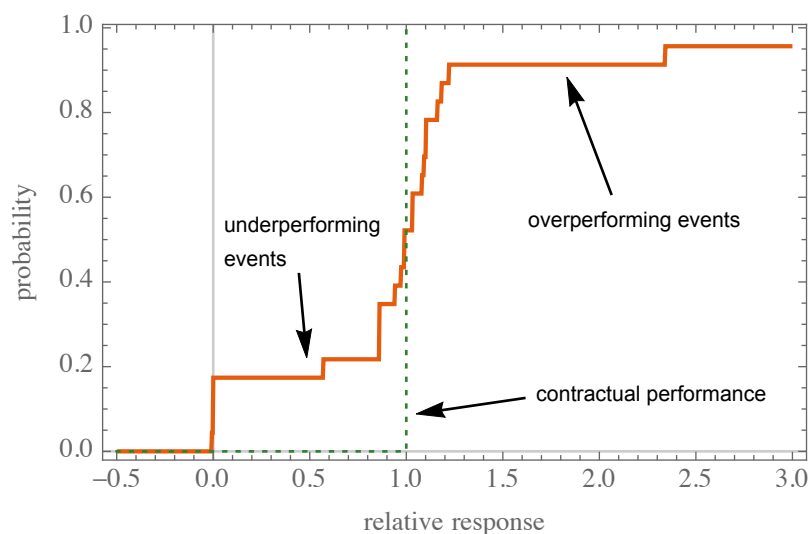


In the remainder of the chapter, we restrict our analysis to the stable response after the initial transient. The response of each site to a given event is averaged across the period in question (to the right of the dashed line in Figure 13), thus reducing it to a single value. This value reflects the achieved response and is therefore most relevant for quantifying I&C DSRs’ ability to provide prolonged load reduction.

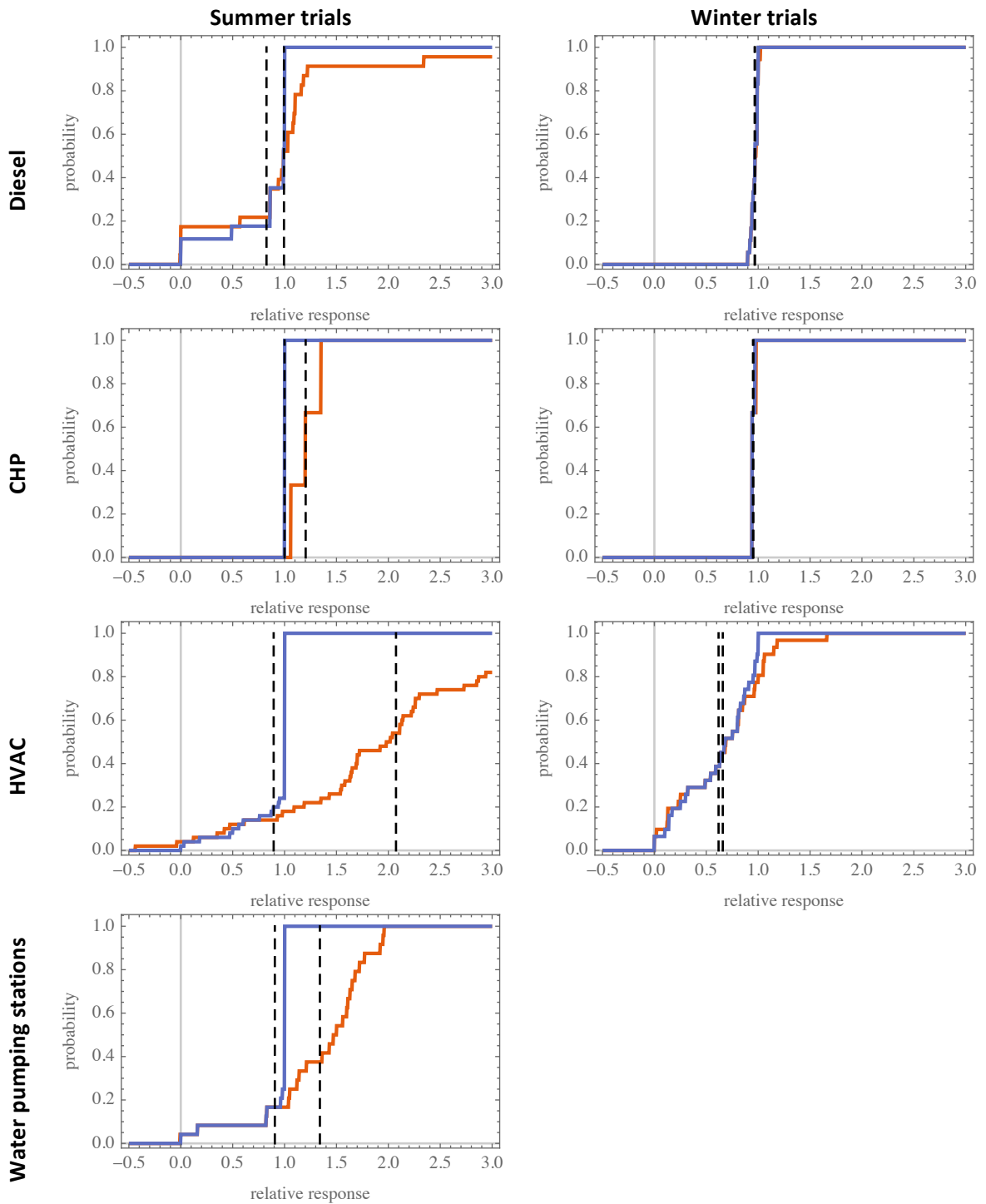
### 3.2 Statistical dependability analysis of aggregate units

It was shown in the previous section that generation-led and demand-led responses have fundamentally different response characteristics, and further differences occurred between summer and winter trials. The typology with seven different *event classes* as introduced in Table 2 and Figure 13 will be used throughout this chapter to illustrate the resulting differences on aggregate site performance.

As a first step the performance for each site and event was quantified by averaging the site’s relative performance over the stable response duration of the event, as defined per event class. This resulted in a set of numbers for each event class. Those numbers (across relevant sites and events) were assumed to be independent realisations of an underlying probability distribution for each event class. The observations were then used to define an empirical probability distribution: each outcome was considered an equally likely outcome of a random response. The resulting probability distributions are shown in Figure 14, in the form of cumulative distribution functions (CDFs). Their values for a response value  $r$  indicate the probability that a response of  $r$  or less than  $r$  is realised. By definition, the curves start at 0 on the left and end at 1 on the right. A guide to their interpretation is shown below, with the contractual performance (value 1) indicated by a green dotted line.



The statistical analysis described above was performed in two variations. First, the observed responses were clipped to the interval  $[0,1]$  before averaging. This reflects the ‘contractual’ point of view, where a load reduction in excess of the contracted amount is ignored. In this case, the measured average response always lies within the range  $[0,1]$  and can be considered a measure of compliance. The second analysis approach does not perform this clipping. Because this measures the *actual* load reduction on the network this is arguably the perspective that is more suitable to DNO constraint management.



**Figure 14 Empirical probability distributions and the effect of clipping**

Figure 14 shows the cumulative distribution functions obtained with both approaches, with the clipped results in blue and the unclipped results in red. The respective mean response values are shown using dashed vertical lines, where the larger value corresponds to the unclipped response. It is clear the use of clipping in the analysis has very significant effects on the inferred probabilistic model. The difference is especially pronounced for the HVAC units in summer, where responses up to 6 times the contracted value have been observed, and the mean response was more than twice the contracted value. As will be investigated in the following section, this tendency to outperform contract specifications has a substantial effect on the number of units needed to produce a desired response, and may fully offset the lack of dependability of independent units.

It is worth pointing out that the number of independent sites involved in the trials was limited, as was the number of trial events, so that statistical fluctuations have a substantial impact on reported results. This is especially true for the CHP curves, which are based on three events for a single site each. Furthermore, involvement in the trials has led to substantial opportunities for learning, the effects of which cannot be disambiguated from seasonal effects between summer and winter trials. For these reasons, the range of results from the quantitative analysis should be taken as an indicative of the type and variability of performance that might be encountered.

The probabilistic models shown in Figure 14 may be used to construct probability models for multiple units. In the following we will consider aggregates of  $N$  identical but independent units belonging to the same event class. The probability density function (PDF) of the  $N$  sites is obtained by repeated convolution of the relevant single-site PDF. The resulting distributions (rescaled for ease of comparison) for  $N=1,2,5,20$  units of the *HVAC summer (unclipped)* type are shown in Figure 15. As expected, variability reduces for larger aggregations of units, and the per-unit aggregate response converges to the mean.

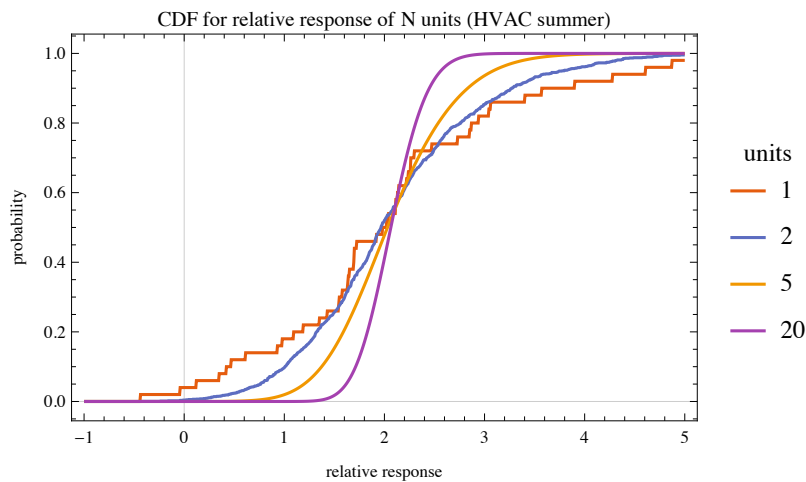


Figure 15 Response of independent aggregate units (HVAC summer, unclipped)

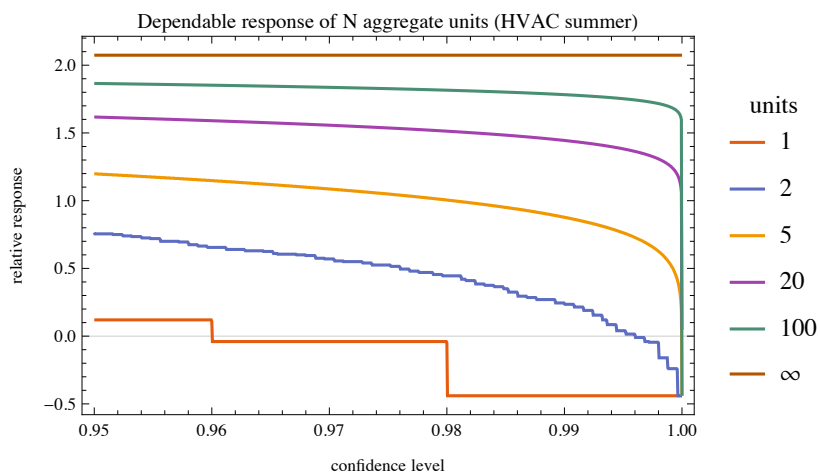


Figure 16 Dependable response of independent aggregate units (HVAC summer, unclipped)

Of particular relevance to reliability analysis in the context of network constraint management is the lower left corner of this graph, which relates very low response levels to their probability of occurrence.

Ideally, a DNO relying on I&C DSR should quantify the probability that a certain response target will be met – the *dependability* – and adjust its decisions to achieve acceptable level of risk. In practice this involves an inversion of the relation shown in Figure 15: the horizontal axis becomes the desired *confidence level*, i.e. the desired probability that a response will be achieved, and the vertical axis is the corresponding *dependable response*. Figure 16 plots the dependable response for confidence levels in the range [0.95, 1] for the *HVAC summer (unclipped)* event class and  $N$  independent units. Note that the dependable response may be negative for high confidence levels and few units of this type, but it increases steadily with  $N$  and eventually approaches the average response value.

### 3.3 Unit commitment requirements

The definition of dependable response enables us to address the challenge that is directly relevant for network constraint management: if a load change of a given magnitude is required, how many units need to be committed to reliably deliver this response? Clearly, the answer to this question depends on the desired confidence level, with higher confidence levels requiring more units to be committed in order to hedge against unresponsive sites. For this analysis, the response will be expressed in ‘contract units’, where 1 is the target response of a single unit. All units are independent and drawn from the same event class distribution. The procedure can be illustrated using Figure 16, where determining the unit commitment requirement corresponds to increasing the value of  $N$  until the corresponding curve exceeds the target response value at the desired confidence level.

Figures 17 and 18 show the computed commitment requirements for all event classes and a range of required contract units. Figure 17 shows results for probability distribution that were computed from clipped responses, where performance exceeding the contract is ignored; Figure 18 shows results obtained without clipping. The upper-left half of each graph has a pink background colour and indicates the region in which overprovisioning is required: to achieve a dependable response of  $N$  units, *more than  $N$*  units must be committed. The dotted line indicates the contracted response (in whole units). Finally, each plot shows three curves, for confidence levels of 90%, 99% and 99.9%.

A number of conclusions can be drawn from these plots:

- When the measured responses are limited to the [0,1] interval, some amount of overprovisioning is always required.
- When responses are not clipped and the mean performance exceeds the contract, underprovisioning is a viable strategy for sufficiently large desired responses.
- For CHP and diesel units (winter trials), performance is very close to the ideal as specified by the contract. However, diesel performance during the summer trials was significantly worse, caused by a few late- and non-start occurrences. There is no evidence to suggest that this was specific to the summer trials, so this illustrates the sensitivity of these empirical models (and extrapolations to future performance) to statistical fluctuations.
- HVAC units performed significantly better in summer than in winter.
- Higher desired confidence levels result in larger unit commitment numbers. The sensitivity to confidence levels depends on the variability of the single-unit response.

Figure 17 Unit commitment requirements (clipped response)

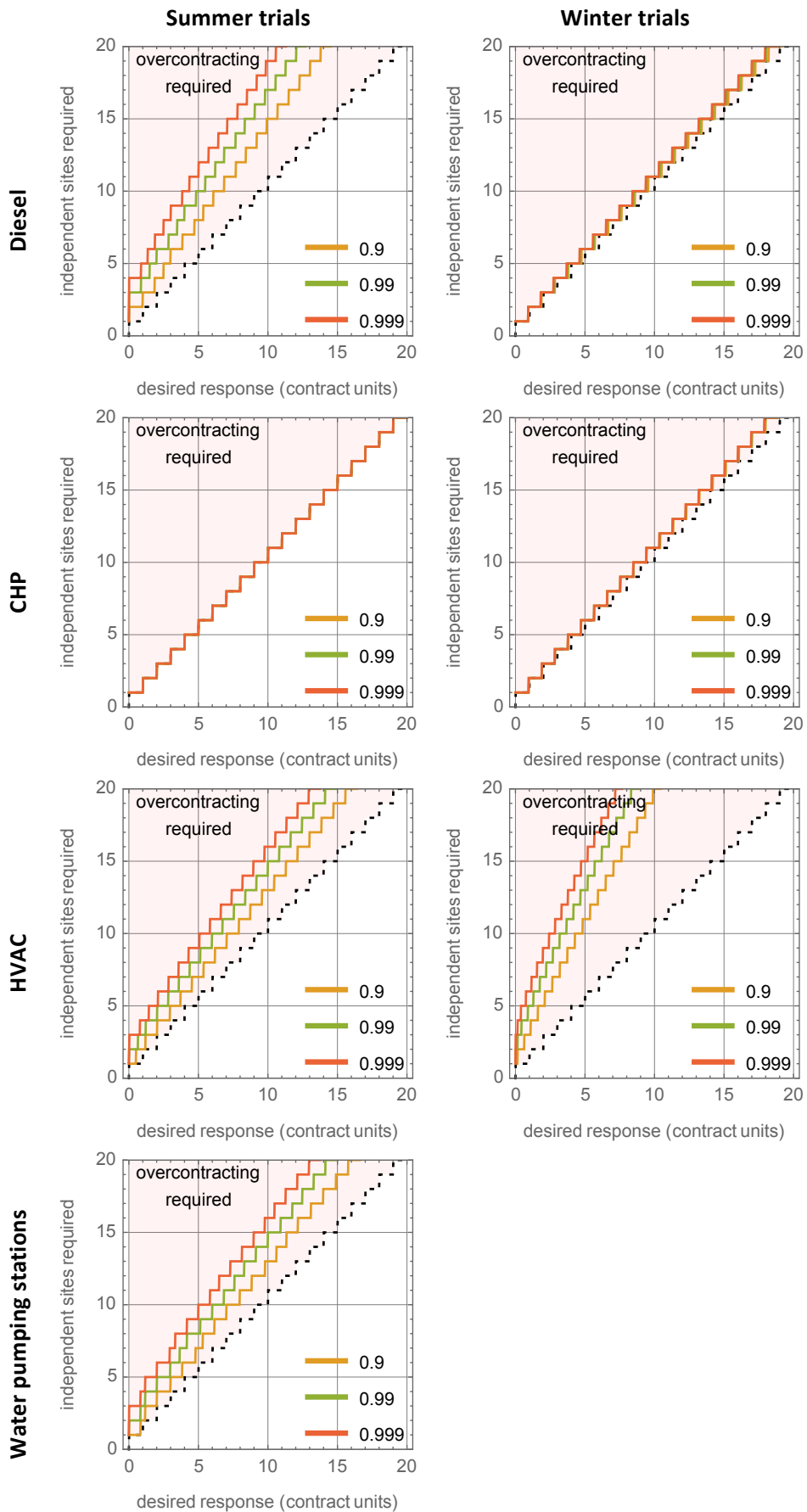
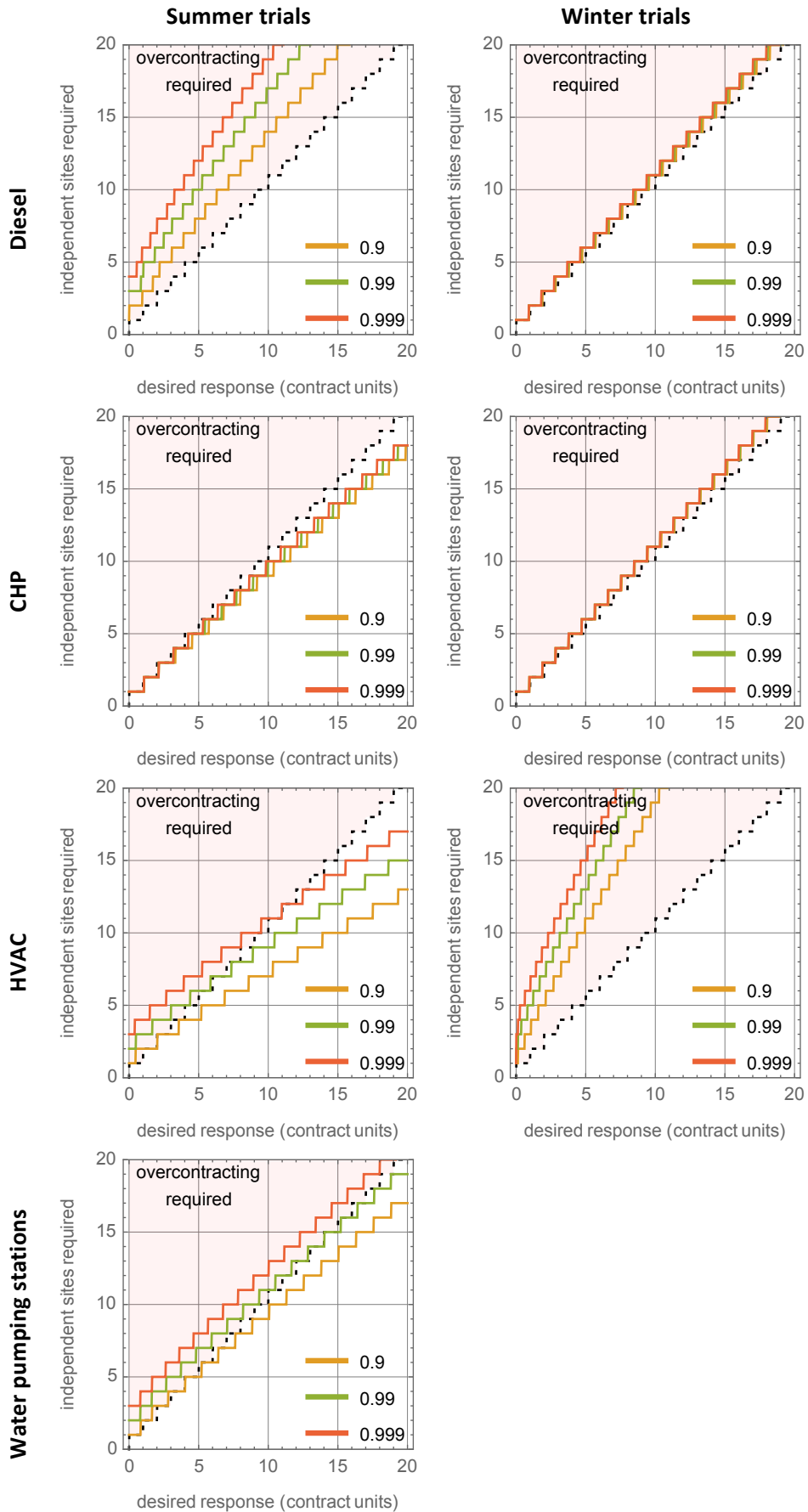


Figure 18 Unit commitment requirements (no clipping)



### 3.3.1 Analytical approximation

The unit commitment graphs are the result of iterative convolution and scanning for the minimum number of units that satisfies a performance constraint. This approach has two drawbacks: it is not trivial to implement, and the relation between the computed curve and the input parameters (performance of a single unit) is not easy to interpret.

In this section we present an analytical approximation to the direct convolution approach. It provides a means to gain insight into the drivers of aggregate performance, and how various interventions may affect it. Furthermore, the approximation is demonstrated to provide a good fit for the event classes under consideration.

The analytical approximation builds on our understanding in two limits where exact analytical results are available: for very small and very large desired response values. Those limits are discussed below, and are then integrated into a single model.

#### The small response limit

The small response limit considers how many units are required to generate *any* non-zero response, given a confidence level  $c$ . This is equivalent to computing the required number of units  $N_{>0}$  such that the probability of *none of these* units responding is smaller than  $1 - c$ . Assuming the absence of negative response values, the answer is given by

$$N_{>0} = \left\lceil \frac{\log(1 - c)}{\log P_0} \right\rceil$$

where  $\lceil \cdot \rceil$  denotes the ceiling function that selects the nearest larger integer and  $P_0$  is the probability of a single unit failing to respond (zero response level). Note that this approximation assumes the absence of negative response values.

#### The large response limit

The second case is the limit where a large number of units is committed. The response of  $N_{lim}$  committed units is a sum of independent identically distributed random variables, which for sufficiently large  $N_{lim}$  may be approximated by a normal distribution using the central limit theorem. The asymptotic dependable response  $N_{resp}$  is therefore given by

$$N_{resp} = \mu N_{lim} - z_1(c)\sigma \sqrt{N_{lim}}$$

Here,  $\mu$  and  $\sigma$  are the mean and standard deviation of the single unit response, respectively.  $z_1(c)$  is the z-value corresponding to the 1-sided confidence interval for confidence level  $c$ . To determine the desired unit commitment  $N_{lim}$  in terms of the desired output  $N_{resp}$ , the above equation must be inverted, resulting in

$$N_{lim}(N_{resp}) = \frac{N_{resp}}{\mu} + \frac{1}{2} \left( \frac{z_1(c)\sigma}{\mu} \right)^2 \left( 1 + \sqrt{1 + \frac{4\mu N_{resp}}{(z_1(c)\sigma)^2}} \right)$$

#### Combined model

The two limits described above are combined into a single model for determining the approximate unit commitment  $N_{comm}(N_{resp})$ . A simple heuristic is used: the asymptotic response is used *as is*, unless



doing so violates the constraint posed by  $N_{<0}$ , in which case a constant is added. Visually, the curve  $N_{lim}(N_{resp})$  is shifted upwards to accommodate the constraint  $N_{comm} \geq N_{<0}$ , and in equation form:

$$N_{comm}(N_{resp}) = N_{lim}(N_{resp}) + [N_{<0} - N_{lim}(0)]^+$$

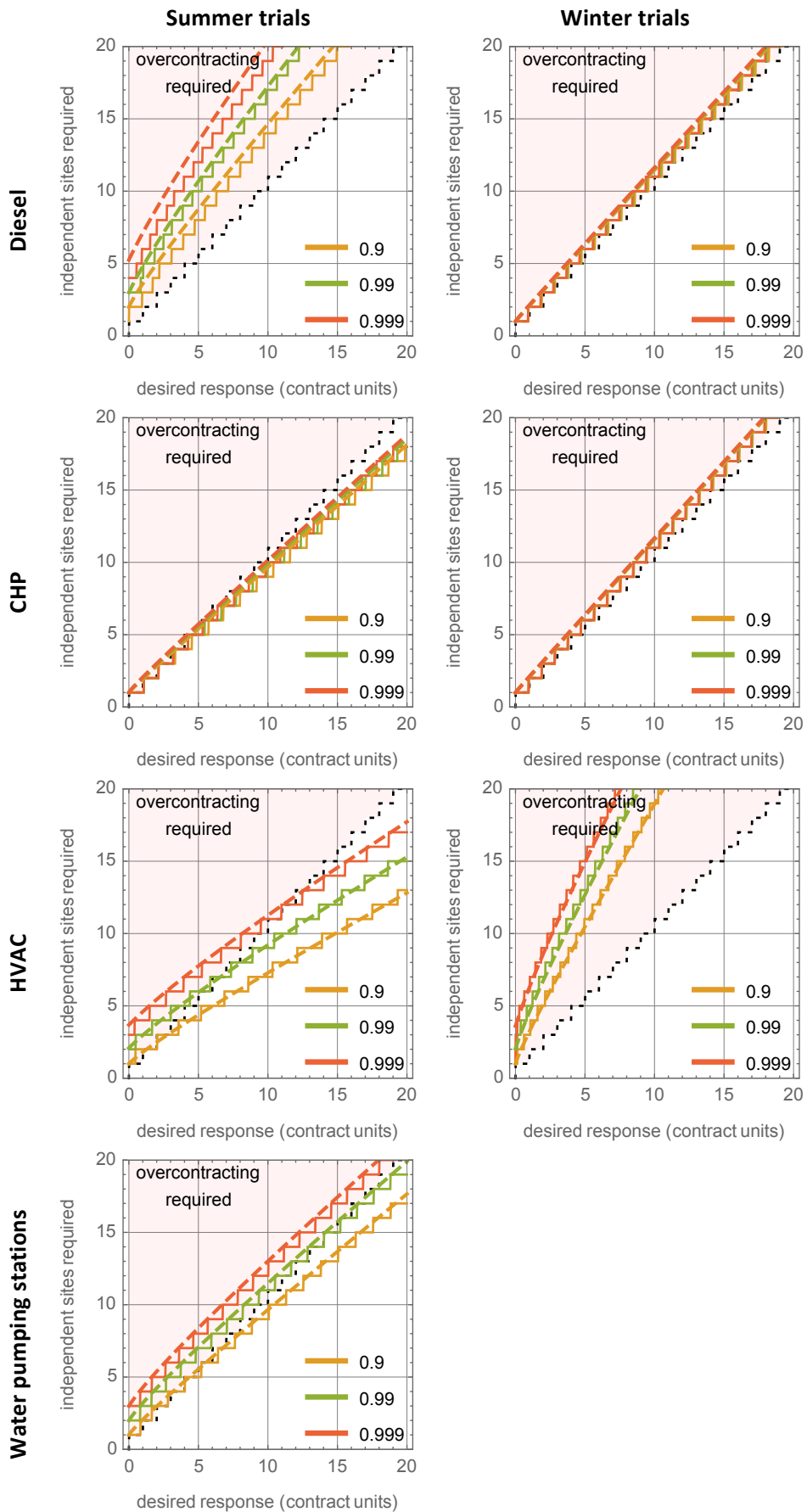
The operator  $[\cdot]^+$  indicates that only the positive part is taken.

We emphasize that the model not a fit, but a computed curve based on three model-specific parameters: the mean response  $\mu$ , the standard deviation  $\sigma$  and the zero-response probability  $P_0$ . For event classes where negative responses are possible,  $P_0$  is taken to be the probability of a response smaller than or equal to zero. This approximation is expected to be reasonable as long as the negative response events are rare and limited in magnitude.

Results obtained with the approximate analytical model for all event classes (unclipped) are shown in Figure 19. For all event classes and the three confidence levels under consideration, the model provides a good fit to the explicit convolution solutions across the entire interval. Furthermore, for the cases considered the model is shown to be conservative (when discretisation is taken into account), meaning that it will not undercommit units compared to the true solution. Furthermore, with the exception of diesel generators in the summer, the model provides a tight bound resulting in very little overcommitment of generators.

These results suggest that the model may be used as a shortcut to performing full convolutions, especially when absolute accuracy is not required. For example, it may be used to develop an intuitive understanding of the impact of single-unit response parameters on aggregate behaviour. Alternatively, because an algebraic expression is available it may be embedded in simulations and/or optimisation frameworks as an approximation of the true number of required units.

Figure 19 Analytical approximations for unit commitment requirements (no clipping)



### 3.4 Common mode failures

The analysis in this chapter up to this point has assumed independence of the responses from different sites. This way, even highly unreliable sites can produce a dependable response, as long as units are committed in sufficient numbers. However, there are concerns about the veracity of the independence assumptions. In particular, it is well-established that engineering reliability studies should consider the potential impact of common mode failures that simultaneously affect multiple components.

In case of network constraint management such common modes may occur upstream of the actual sites: they could include failures by the DNO control room to send the required signal, failures by the aggregators to trigger the required responses in contracted units under their control, or malfunctions in the communications systems – either locally or affecting many sites at once. For example, a total loss of communication (telephony and internet) at an aggregator office may interfere with its ability to control the assets in its portfolio – and most aggregators will have redundant systems in place to offset such failure modes. In addition, external factors may affect the availability of sites in a more gradual manner. For example, the outside temperature affects both the available response from HVAC and CHP sites.

As evidenced by this short description, a detailed treatment of common mode failures requires domain-specific modelling supported by large amounts of relevant failure data. The Low Carbon London trials were not set up specifically to investigate this issue, but nevertheless analysis of the time traces has identified three events that may show evidence of degraded performance with a common origin. One example is shown in Figure 20, which shows the observed consumption of three HVAC sites during an event on 21 August 2013. The three sites, which are controlled by the same aggregator, were supposed to reduce their power consumption at time 0 on this graph. Instead, they all reduced their power consumption within a short time span after 15 minutes. This suggests a delayed activation resulting from an issue within the DNO-aggregator control chain.

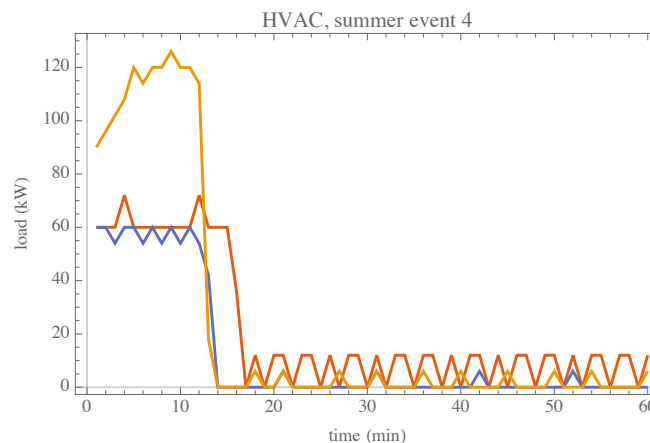


Figure 20 Potential common mode event (21 August 2013)

As mentioned, there is insufficient data to generate an empirical model of common mode failures. Instead, the potential impact of common mode outages is investigated using a schematic model. In this model, depicted in Figure 21, common mode failures are the result of an aggregator to forward response signals to sites under their control, with a probability of 0.5% (1 in 200).  $N$  sites are assumed to be controlled by  $M$  aggregators, with  $M \leq N$ . The sites are evenly distributed across aggregators, with deviations up to 1 permitted to accommodate all values of  $N$ .

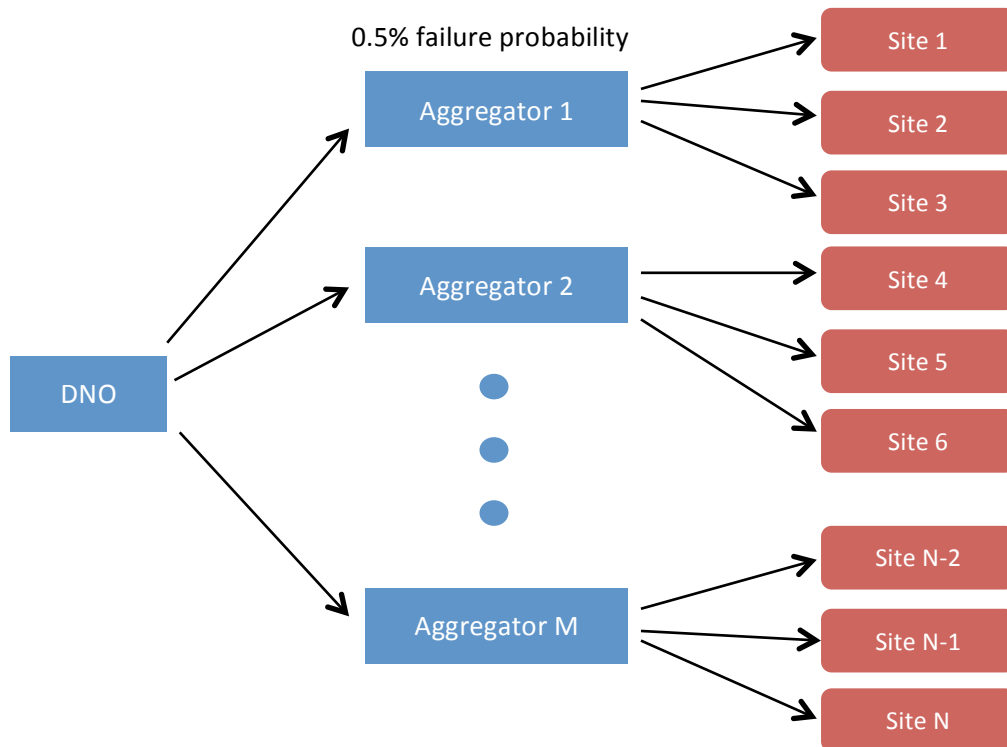
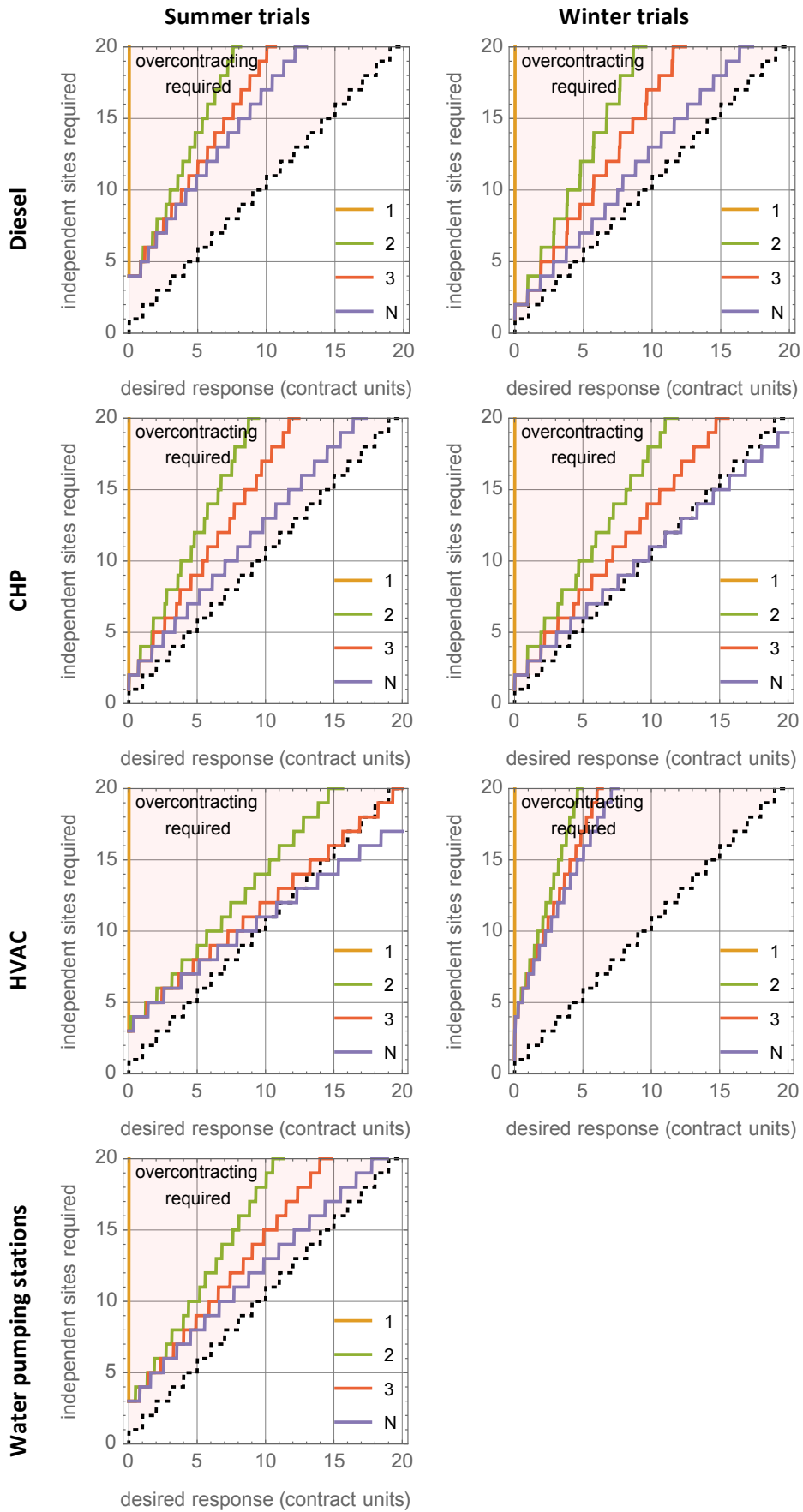


Figure 21 Schematic depiction of common mode failure model

Figure 22 shows the resulting unit commitment requirements, for all event classes (no clipping). Each panel contains curves for  $M = 1, 2, 3, N$  aggregators, where the choice  $M = N$  corresponds to one aggregator per site, restoring independence. A desired confidence level of 99.9% was used in all cases. The results show the following:

- Common mode failures have a significant impact on commitment requirements.
- In this case, a single aggregator ( $M = 1$ ) never provides sufficient performance. This is because the 0.5% failure probability of the aggregator exceeds the standard set by the 99.9% confidence level, regardless of the performance of individual units.
- Spreading risks across multiple aggregators results in a large improvement in dependability. In most cases  $M = 3$  is appreciably close to the full independence solution.

Figure 22 Common mode failures (models without clipping)



### 3.5 Demand-led response and payback

Previous sections have analysed the response of sites during the event. This section considers the aftermath of load-reduction events by HVAC devices, which often showed steep power spikes after the end of the event. This effect is known as a 'load recovery' or 'payback'. It was first described and studied in relation to the residential demand-side response exercised by domestic appliances operating as thermal loads (e.g. fridges, water heaters and air-conditioners) [16][17]. Observed load spikes are stipulated by the operational principle of such devices [18]. The provision of demand reduction causes a drift away from the temperature setpoint, and after the demand reduction event, such devices tend to quickly ramp up their power consumption in order to re-establish the regular operating temperature (e.g. to restore temperature level in the room as it was before load reduction actions started). A schematic illustration of a load recovery pattern is shown in Figure 23.

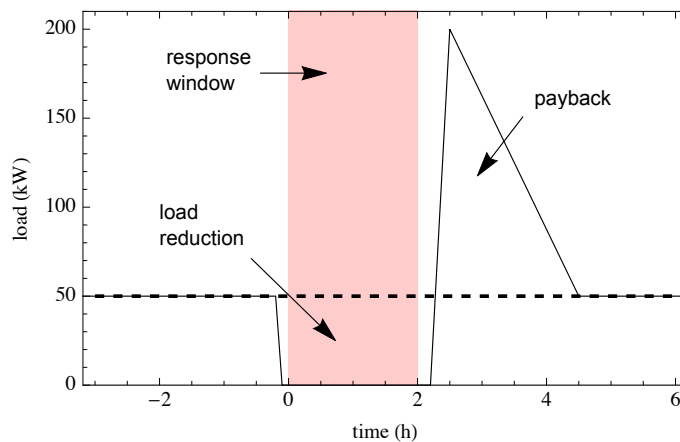


Figure 23 Schematic illustration of demand response payback

Figure 24 shows payback traces for HVAC groups (summer and winter respectively), constructed in a similar manner to the response traces in Figure 13. A 2-hour interval (200% of the event time) was chosen based on the observation that after 2 hours the effect mostly or entirely disappears, and data was sorted into 40 bins instead with identical resolution. The starting point for each trace is the scheduled end of the DSR-event.

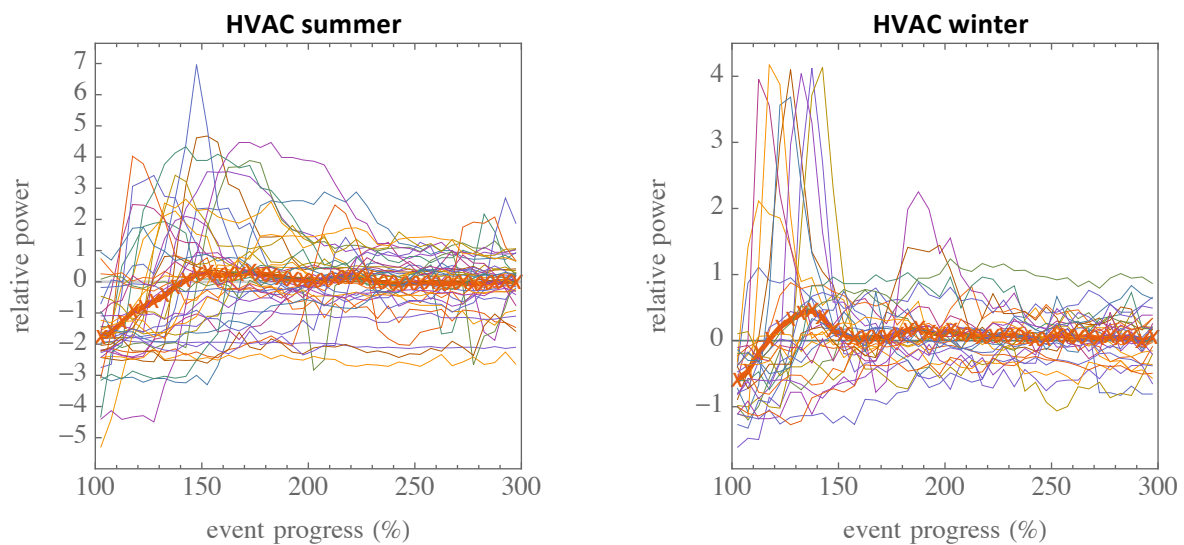


Figure 24 After-event response traces, illustrating feedback

The traces show a large variation of payback behaviour, with differences in peak height, width and initiation time. The distribution of payback peak magnitudes (normalised to committed capacity) across sites and events is presented in Figure 25. Site numbers correspond between summer and winter trials; events with no visible response were not considered. It is clear that although the payback magnitude is highly variable overall, the range across which it fluctuates is site-dependent. Site 4 in particular frequently demonstrated peak demand levels in excess of four times the contracted load reduction amount. Other sites – site 10 in particular – achieve payback levels that are less than the contracted amount. The overall averages were 2.3 and 1.75 times the contracted response for summer and winter trials respectively (with extreme values of up to 5-8 times of contracted response).

Clearly, the large payback peaks can pose difficulties for the DNO, especially when sites are used for prolonged constraint management. This is different from the business-as-usual use case for I&C DSR in supporting the national network, where payback peaks can be distributed. In the DNO context it would seem reasonable to profile a site’s ‘payback signature’ as part of the sign-up process, and perhaps subject it to contract terms.

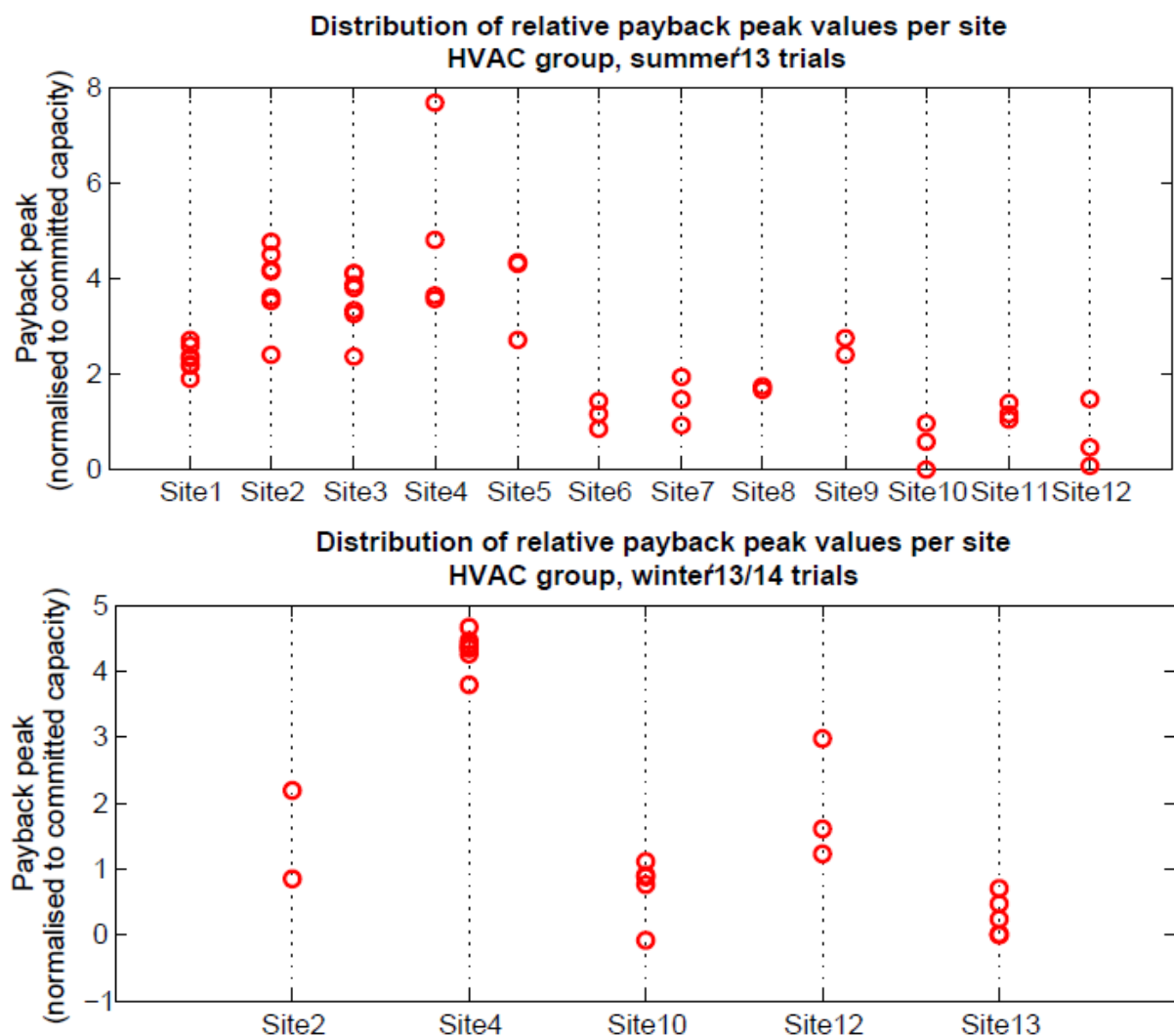


Figure 25 Payback peak magnitude for HVAC units, summer (top) and winter (bottom)

### 3.6 Summary and discussion

This chapter has analysed the reliability performance of I&C DSR as evidenced in the Low Carbon London trials. Probabilistic models were constructed and analysed in order to quantify the dependability of I&C DSR for network constraint management.

First, the measured response traces for all sites and each of the trial events were analysed. The variability, magnitude and seasonal dependence of I&C DSR was found to be distinctive for each of the four classes considered: diesel, CHP, HVAC and water pumping stations. Generation-led DSR (diesel and CHP) was found to respond most in line with the contract targets, consistent with their direct control over load levels. The response of demand-led DSR (HVAC and water pumping stations) is more variable, both in terms of average magnitude and the inter-event variation. The response of HVAC and CHP systems differed between summer and winter trials. HVAC demonstrated much larger response magnitudes – and variability – in the summer trials, than in the winter trials. This is consistent with the larger dependence on air conditioning in the summer months, allowing for larger reductions.

Probabilistic response models were constructed for each DSR type, and separately for the summer and winter trials. The aggregate response of multiple independent units was considered and unit commitment requirements were computed and visualised for a range of target load reductions. It was found that a significant fraction of sites outperformed the contract terms, with HVAC sites during summer having the strongest performance, with reductions up to six times of the contracted amount. The decision whether to take this bonus into account for the construction of probabilistic models has significant implications for aggregate performance metrics.

The numerically computed unit commitment graphs do not provide intuitive insight into the relation between model parameters and aggregate dependability. For this reason, an analytical approximation was developed for the unit requirement curve of independent identical aggregates of DSR sites. A good match with the numerically computed curves suggests that the model may be used as a shortcut to performing full convolutions, especially when absolute accuracy is not required. For example, it may be used to develop an intuitive understanding of the impact of single-unit response parameters on aggregate behaviour, or to embed approximate dependability characteristics in a larger simulation.

Analysis of the response traces also evidenced the occurrence of simultaneous late-start events, involving sites being triggered by single aggregators. This reinforces the need to understand the potentially severe impacts of common mode failures in network management. A basic model for common mode outages was introduced, where sites are distributed over a small number of aggregators. A probability of just 0.5% for the failure of an aggregator to activate its DSR sites has a very large impact on the unit commitment requirements. Depending on the desired confidence level, using a single aggregator may never provide sufficient dependability, whereas good performance is recovered with the use of three independent aggregators.

Finally, it has been noted that demand-led DSR may take the form of demand shifting, where the initial demand reduction is followed by a payback phase in which the load increases with respect to the baseline. If DSR is used for constraint management by the DNO, the payback effect may result in postponing rather than resolving the network constraint. In the LCL I&C DSR trials payback peaks have been observed with a magnitude up to 8 times the contracted load reduction. The peak magnitude is highly variable, but generally characteristic for the site. It would seem reasonable for the DNO and



aggregator to profile a site's 'payback signature' as part of the sign-up process, and perhaps subject it to contractual limitations.

## 4 Network reliability modelling: methodology

The present distribution network planning standard, Engineering Recommendation P.2/6 (abbreviated to 'P2/6') [38], defines the acceptable durations of supply outages following first and second circuit outage conditions as function of group demand. In addition, P2/6 specifies a capacity value for distributed generation (DG) to be used in future circuit capacity planning. The capacity values for the contribution of DG are derived using a probabilistic calculation which is explained in [37]. This method is denoted as 'Equivalent Circuit Capacity' (ECC) in [36]. Based on a range of successful demonstration and trials carried out by Low Carbon London, UK Power Networks has developed a number of DSR schemes designed to substitute for network reinforcement. The capacity contribution of these DSR schemes is quantified following the philosophy of the present ER P2/6 used to calculate capacity contribution of DG.

In this work, based on trials conducted in Low Carbon London, the contribution of DSR to security of supply is assessed using a probabilistic risk modelling framework to further inform a number of topics:

- Contribution of DSR technologies to security of supply in a network context,
- Strengths and weaknesses of P2/6 in estimating the contribution of DSR to security of supply,
- Benefits of contractual redundancy,
- Impact of DSRs coincidence in delivery (common mode failures) on contribution to security,
- Impact of DSR scale / magnitude on the contribution to security of supply.

### 4.1 Background

The response and number of dispatches of DSR technologies demonstrated in Low Carbon London are shown in Table 4. There were a total of five CHP facilities with a total capacity of 6,695kW, three diesel-generating units with a total capacity of 6,000kW and 17 demand-led DSR facilities with a total demand reduction capability of 3,330kW.

Table 4: DSR facilities requested responses. Source: [40]

| Type                  | Installation | Requested response (kW) |
|-----------------------|--------------|-------------------------|
| <b>CHP</b>            | DR005        | 2000                    |
|                       | DR024        | 2000                    |
|                       | DR029        | 1500                    |
|                       | DR036        | 1000                    |
|                       | DR079        | 195                     |
| <b>CHP Total</b>      |              | <b>6695</b>             |
| <b>Diesel</b>         | DR001        | 2000                    |
|                       | DR002        | 3000                    |
|                       | DR035        | 1000                    |
| <b>Diesel Total</b>   |              | <b>6000</b>             |
| <b>Demand-led DSR</b> | DR011        | 30                      |
|                       | DR012        | 20                      |
|                       | DR023        | 20                      |
|                       | DR027        | 200                     |
|                       | DR028        | 50                      |

| Type                        | Installation | Requested response (kW) |
|-----------------------------|--------------|-------------------------|
|                             | DR031        | 220                     |
|                             | DR032        | 190                     |
|                             | DR034        | 90                      |
|                             | DR037        | 80                      |
|                             | DR041        | 350                     |
|                             | DR042        | 200                     |
|                             | DR043        | 800                     |
|                             | DR044        | 300                     |
|                             | DR045        | 300                     |
|                             | DR047        | 100                     |
|                             | DR053        | 180                     |
|                             | DR068        | 200                     |
| <b>Demand-led DSR Total</b> |              | <b>3330</b>             |

Figure 26 to Figure 28 show the average individual and aggregated state probabilities for diesel, CHP and demand-led DSR facilities, respectively. These are created from Low Carbon London I&C DSR trials data [40].

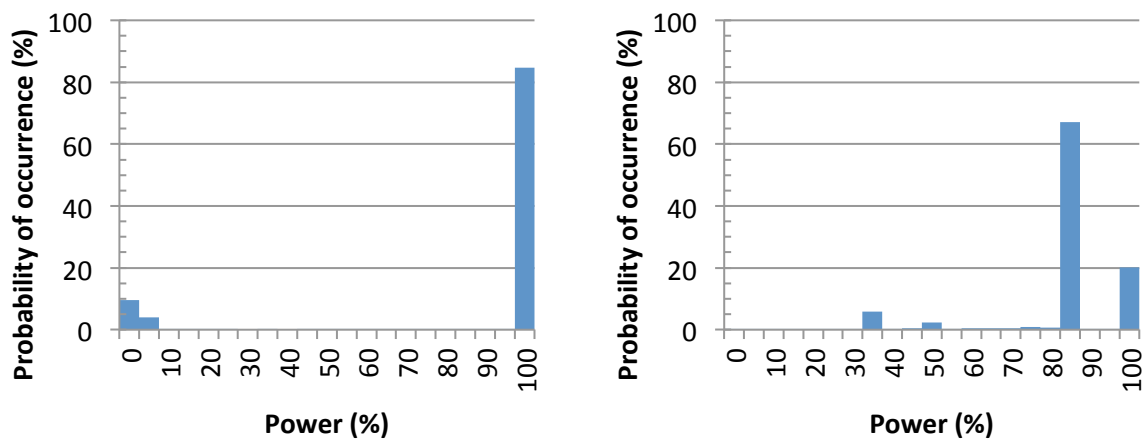


Figure 26: Diesel average individual (left) and aggregated state probabilities. Source: [19]

For example, probability of average individual diesel facility to deliver more than 97.5% of contracted capacity is about 85% and to deliver less than 2.5% is about 10%. On the other hand, for all three diesel facilities probability of delivering more than 97.5% of total contracted capacity is about 20% and to deliver less than 2.5% is practically negligible. It can be seen that three diesel facilities will deliver between 82.5-87.5% of their contracted capacity with the probability of about 67%. This shows that the individual facilities tend to deliver high and low power percentage with higher probability whilst when aggregated the probability of delivering 100% of contracted power or not delivering any contribution reduces. For more details see [19].

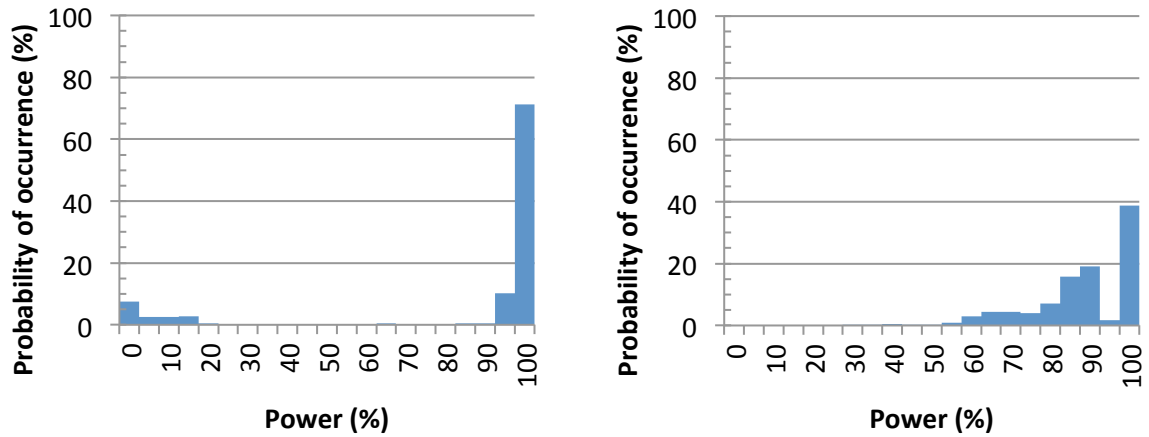


Figure 27: CHP average individual (left) and aggregated state probabilities. Source: [40]

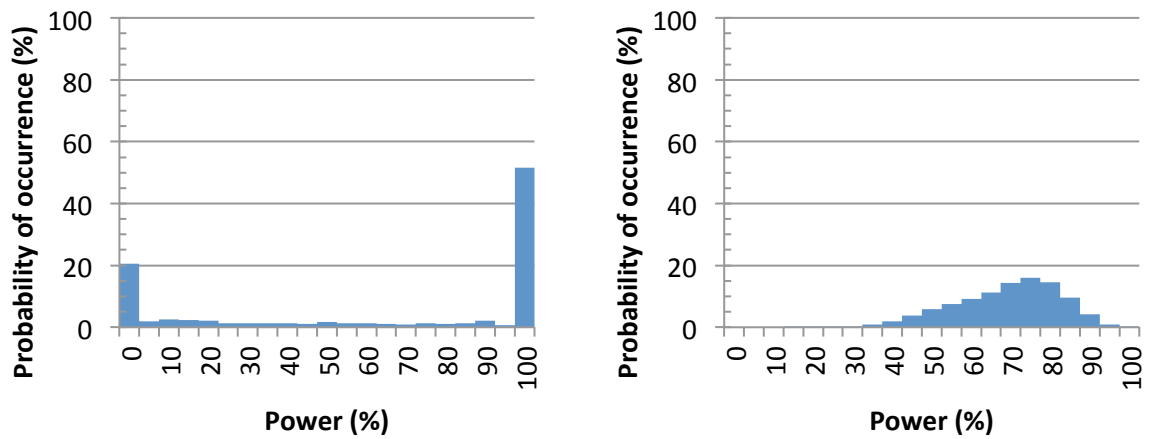


Figure 28: Demand-led DSR average individual (left) and aggregated state probabilities. Source: [40]

The load duration curves for eight primary substation sites are created and then approximated by piecewise linear curves, as shown in Figure 29 [40].

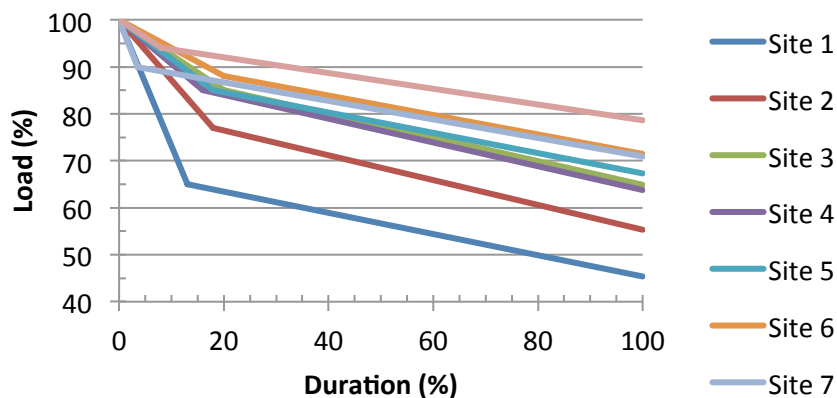


Figure 29: Individual LDC for eight primary sites. The load factor is between 59% and 87%. Source: [40]

Figure 30 shows the piecewise approximation of the average load duration of the above mentioned eight primary sites [40].

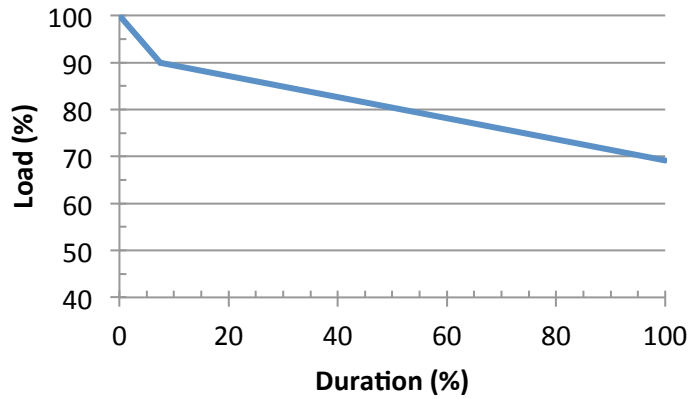


Figure 30: Average LDC of eight primary sites. The load factor is 81%. Source: [40]

The ‘Equivalent Circuit Capacity’ (ECC) approach, described in P2/6 [38], is used to estimate the contribution of DSR to security of supply, as illustrated in Figure 31. The network is represented by a single bus bar which carries a variable load  $D + \Delta D$  that is supplied by one or more circuits with a finite total capacity  $X$ , assisted by a DSR that is represented by a random variable  $Y$ . The reason for modelling with a random variable is that, as shown in Figure 26 through Figure 28, the demand reduction can vary from event-to-event and throughout an event. Load  $D$  is the part of the load which can be securely supplied from circuits and  $\Delta D$  is the part of the load which can be securely supplied from DSR. The procedure described in P2/6 involves finding the value of the risk indicator (in this case Expected Energy Not Supplied indicator (EENS<sup>4</sup>)) for a portion of demand ( $D_Y$ ) deemed to be supplied from DSR facilities (excluding network circuits). Then the ideal, never fails, source of ECC, which, when substituted for DSR facilities, will produce the same value of the risk indicator, is calculated. The ‘contribution’ of DSR to security of supply is then the capacity of this ideal source of ECC, which is equal to  $\Delta D$ .

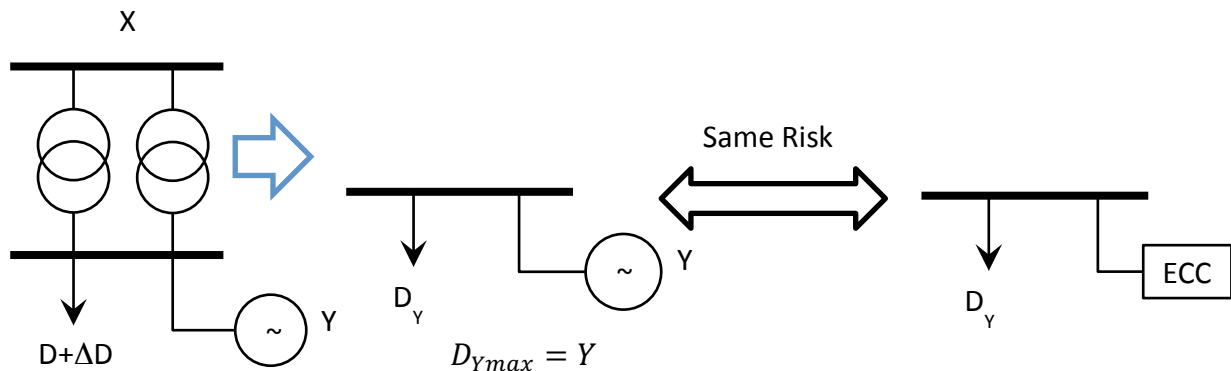


Figure 31: Illustration of the Equivalent Circuit Capacity (P2/6) approach

The state probabilities and load duration curves are used in the following case studies in [40]:

- Impact of load duration curve (LDC) shape on security of supply where aggregated state probabilities per DSR type (diesel generators, CHP and demand-led DSR) and individual LDCs for eight primary sites are used;

<sup>4</sup> EENS provides an expectation of the, typically annually, energy not supplied to customers due to interruptions.

- Impact of number of DSR facilities on security of supply where average state probabilities of a single DSR type facility and the average LDC of eight primary sites are used.

The impact of LDC shape on the contribution to security of supply for eight primary sites and the average LDC is shown in Figure 32. Aggregated DSR probability distributions shown in Figure 26 to Figure 28 are used in the analysis. Sites are denoted with 1 to 8 with LDC shapes shown in Figure 29 whilst 9 denotes the 'average site' for which LDC shape is shown in Figure 30.

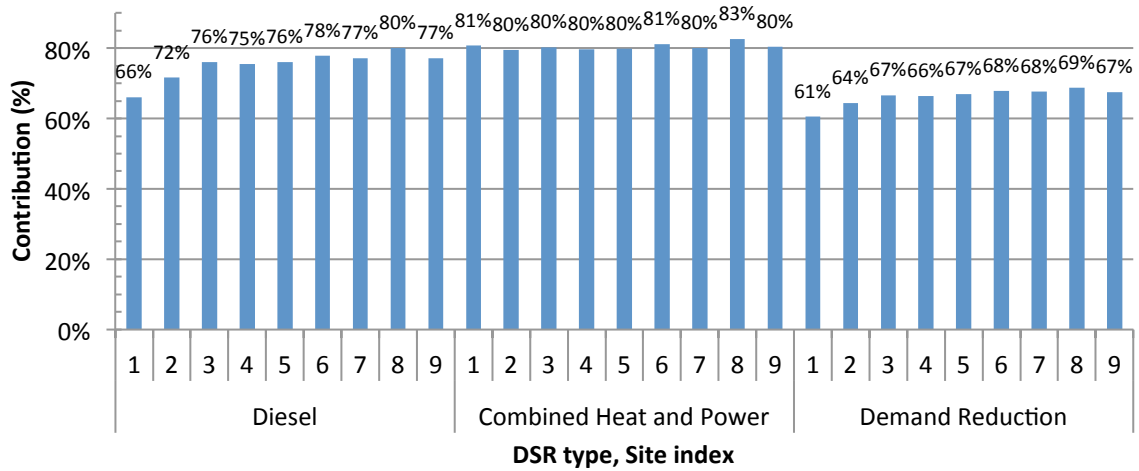


Figure 32: Contribution to security of supply for different types of DSR facility and different LDC shapes where 1-8 denotes site index and corresponding LDC and 9 denotes the average LDC

It can be seen that diesel has a mean contribution around 75%, CHP around 80% and demand-led DSR around 67%. The range of contributions is about 20% ( $\approx(80-66)/((80+66)/2)$ ) for diesel, 10% ( $\approx(69-61)/((69+61)/2)$ ) for demand-led DSR and 4% ( $\approx(83-80)/((83+80)/2)$ ) for CHP. It can be seen that the contribution associated with diesel and demand-led DSR facilities depends significantly on the shape of the LDC, so the actual LDC should be used. However, for CHP the shape of LDC is less important and a generic LDC can be used.

The impact of a number of DSR facilities on the contribution to security of supply is shown in Figure 33. Individual DSR facility COPTs and the average LDC are used in the analysis.

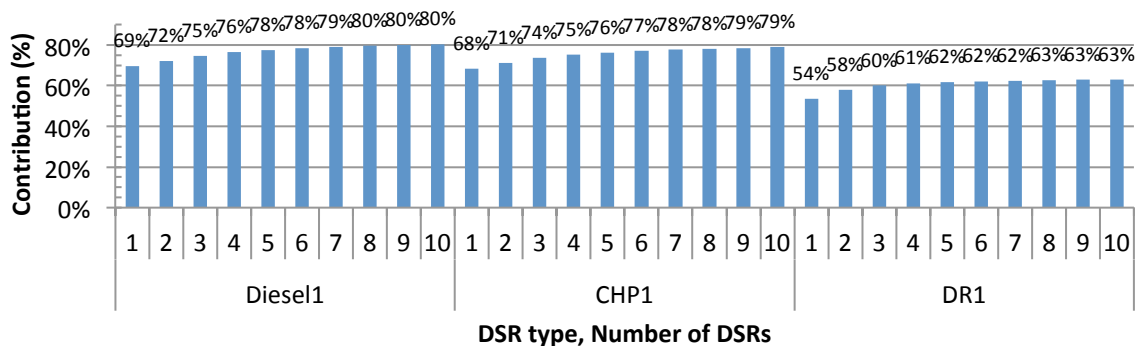


Figure 33: Contribution to security of supply for different types and number of DSR facilities. Number 1 in DSR type represents use of average individual probability distributions.

It can be seen that the range of contributions, depending on the number of DSR facilities, is about 15% (for diesel it is  $\approx(80-69)/((80+69)/2)$  and similarly for other DSR types).

## 4.2 Description of approach

As shown in the previous section, the P2/6 approach applies reliability modelling of individual non-networked technologies without considering the actual distribution network. P2/6 is a minimum standard and several other parts of the regulatory regime in the GB incentivise DNOs to surpass P2/6, particularly in the sense of restoration times after a fault and frequency of faults.

Hence, the P2/6 analysis offers limited insight into the actual reliability implications associated with the use of DSR in particular scenarios. The reason for this is that the reliability delivered to end consumers is ultimately a property of the system as a whole, including the combined effects of the distribution network and DSR. This chapter considers the reliability worth based capacity credit that may be attributed to DSR in a network context.

The conceptual framework underlying the alternative methods used to quantify the security contribution of non-conventional technologies is presented below. A range of concepts has been used historically to establish the security contribution of non-conventional technologies in the generation sector. Concepts of Effective Load Carrying Capability (ELCC) and Equivalent Firm Capacity (EFC) have been widely used, primarily in quantifying the capacity contribution of non-conventional generation technologies in providing security of supply at the national level. These capacity credit contributions are defined as:

- Effective Load Carrying Capability (ELCC) is the amount by which the load may be increased in the presence of DSR facilities while the original risk is maintained,
- Equivalent Firm Capacity (EFC) is the amount of capacity of always available source, which can replace DSR facilities while the supply risk is maintained, and
- Equivalent Network Capacity (ENC) is quantified by increase in network capacity based on equivalent circuit with the reliability performance of the real network, which can replace DSR facilities while the supply risk is maintained.

In most applications, ELCC and EFC approaches are used in the context of the reliability performance of the existing system as a whole to which the non-conventional generation being added<sup>5</sup>. ELCC is defined as the difference in load megawatts between the annual risk functions before and after a unit addition [34]. The risk is typically measured in terms of the annual loss-of-load probability. It has been widely applied such as in generation expansion planning [34], wind power capacity credit [22], [24], [31] and [35] and the capacity value of distributed generation for distribution planning [1], [21] and [36]. This measure is also defined in [28] as the value of allowed load increase facilitated by additional generation connected. In [29] the capacity credit based on ELCC is defined as the amount that the load on each new unit can increase while keeping the same risk of power deficit. In [30] the ELCC of a generator is defined as the amount by which the system's loads can increase (when the generator is added to the system) while maintaining the same system reliability.

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<sup>5</sup> It is important to note this work is focusing on assessing the reliability performance of the distribution networks supported by DSR, but not on the economic case for DSR. However, ER P2/6 will be fundamentally reviewed shortly and it will include consideration of costs of traditional and smart grid solutions (e.g. DSR) in enhancing network capacity and the corresponding benefits delivered to end consumers, so that a business case for alternative solutions to enhancing network capacity can be established. In this context it is conceivable that the incremental reduction in reliability may be acceptable to customers given the benefits of avoided network costs.

EFC is defined as a firm capacity (capacity with 100% availability) that has the same influence on the reliability of supply of the system as the actually installed wind generation [25]. EFC represents the capacity credit of the installed wind generation. In [24] EFC is defined thus: “If an X MW of a power plant gives the same decrease of LOLP as a *100 percent reliable* Y MW power plant, then the capacity credit represented by EFC of the X MW power plant is Y MW”. In [22] the EFC of a conventional or wind power plant is defined as the value of EFC obtained by equating risk values if a hypothetical firm capacity of EFC and if the capacity of non-firm wind or conventional plant is added to the original grid. This capacity credit index is also defined in [28], noting that it is useful to compare wind power and conventional plant with idealised plant having a zero forced outage rate. In [29] the EFC of a generating unit is defined as the capacity of a fictitious 100% reliable unit which results in the same risk index decrease as the generating unit. In [30] the EFC of a generator is defined as the amount of a different fully reliable generating technology (i.e. a generator with a forced outage rate of 0%) that can replace the new generator while maintaining the same system reliability level.

Equivalent Conventional Capacity is defined in [24] thus: “If an X MW of a power plant gives the same decrease of LOLP as a conventional, less than 100 percent reliable, Y MW power plant, then the capacity credit as Equivalent Conventional Capacity of the X MW power plant is Y MW”. This capacity credit index is also defined in [28].

Based on this approach, in this work, the Equivalent Network Capacity (ENC) method that is aimed at quantifying the increase in network capacity based on an equivalent circuit with the reliability performance of the real network rather than a 100% reliable circuit is introduced. In [29] this is defined in a similar manner to the EFC, but in this case the unit is not compared to a 100% reliable unit, but to a reference “conventional” generating unit. In [30] the Equivalent Conventional Power is defined as the amount of a different generating technology that can replace the new generator while maintaining the same system reliability level.

Similarly, capacity saving (CS) is defined as the amount of conventional plant which can be removed from the system after adding renewable generation [28]<sup>6</sup>. Guaranteed Capacity is defined in [41] and referenced in [29] as the least capacity which can be expected to be available with a given probability, referred to as the “level of supply reliability”.

One of the objectives of this work is to compare the levels of capacity contribution that correspond to the different definitions adopted for network adequacy studies:

- Effective Load Carrying Capability (ELCC);
- Equivalent Firm Capacity (EFC);
- Equivalent Network Capacity (ENC);

and to compare these with the capacity contribution attributed to DSR by the present network design standard: P2/6.

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<sup>6</sup> Similar concept can be and are applied to other types of generation; for example the capacity value of micro CHP plant (in economic terms) is greater than those of nuclear technologies, as demonstrated in “Future Network Technologies”, 2006, report to DTI, by G Strbac, N Jenkins, T Green



### 4.3 Effective Load Carrying Capability

The Effective Load Carrying Capability (ELCC) is the amount by which the load may be increased in the presence of DSR facilities while the original risk is maintained.

An illustration of the effective load carrying capability approach is shown in Figure 34. In this approach the value of a risk indicator (Expected Energy Not Supplied (EENS)), including network circuits but excluding DSR facilities, while satisfying the P2/6 (N-1 criteria) is calculated. Then the increase of Group Demand (ELCC =  $\Delta D_{max}$ ) which will produce the same value of risk indicator when DSR facilities are included, while satisfying P2/6 conditions, is calculated. An iterative technique of assuming and then adjusting a Group Demand increase is applied until the desired accuracy of risk indicator is achieved. The contribution to security of supply is then equal to the Group Demand increase.

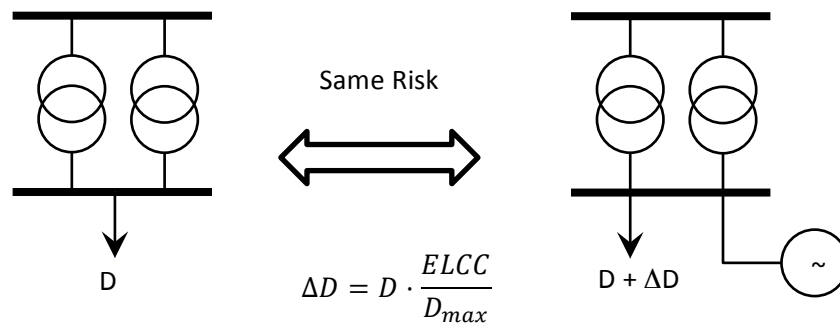


Figure 34: Illustration of the ELCC approach

Figure 35 illustrates the approach.

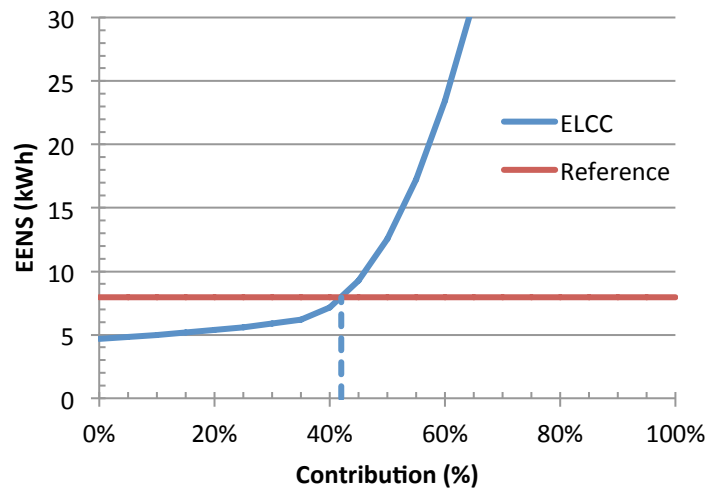


Figure 35: Illustration of contribution of security of supply plotted against a risk indicator (EENS) in the ELCC approach

The X-axis is the assumed contribution (i.e. Group Demand increase); the Y-axis is a risk indicator, EENS. The reference line represents the risk indicator for the system shown on the left in Figure 33. Here the EENS is independent of the contribution. The ELCC line in the figure above represents the risk indicator for the system shown on the right in Figure 33. The EENS increases as the contribution (i.e. Group Demand) increases. The level of capacity contribution to be allocated to DSR will be determined by the point where the two curves cross, which is marked by the dashed line.

#### 4.4 Equivalent firm and network capacities

Equivalent firm and network capacities (EFC and ENC) are the capacities of ideal and real sources, respectively, which can replace DSR facilities without changing the supply risk, as illustrated in Figure 36. In other words, *EFC* is the capacity of a 100% reliable generator, while *RC* is the additional circuit capacity that would result in the same level of risk as the system with DSR facilities. The same analysis can be extended to negative values of *EFC* or *RC* for interventions that may increase load levels, such as EVs and low-price events for dynamic Time-of-Use (dToU) households.

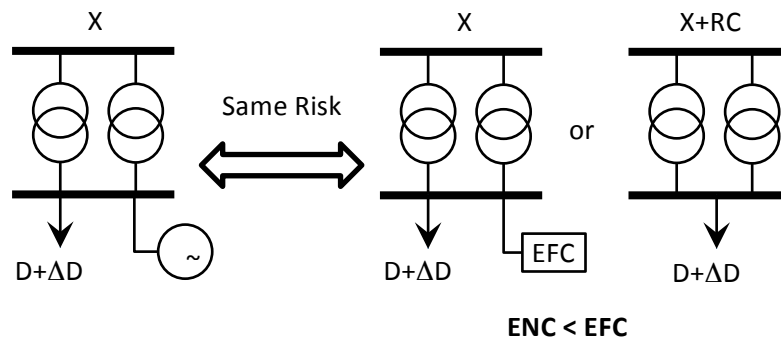


Figure 36: Illustration of Equivalent Firm and Network Capacities

The first step in calculating EFC and ENC is to find the value of a risk indicator ( $EENS_1$ ), including network circuits of total capacity  $X$  and DSR facilities for a Group Demand ( $D_{max} + \Delta D_{max}$ ), which can be supplied while satisfying P2/6 first and second circuit outage conditions for the system on the left hand side in Figure 36. For the EFC approach find the value of a risk indicator ( $EENS_2$ ) when DSR facilities are substituted with an ideal, never fails, source of capacity  $EFC = \Delta D_{max}$  and for the ENC approach find the value of a second risk indicator ( $EENS_2$ ) when DSR facilities are substituted with the increase in total circuit capacity ( $RC = \text{function}(\text{No circuits}, \Delta D_{max})$ ) while satisfying P2/6 conditions ( $ENC = \Delta D_{max}$ ). An iterative technique of finding Group Demand increase is applied until the desired accuracy of risk indices equality ( $EENS_1 = EENS_2$ ) is achieved. The contribution is then given by increase of Group Demand ( $\Delta D_{max}$ ).

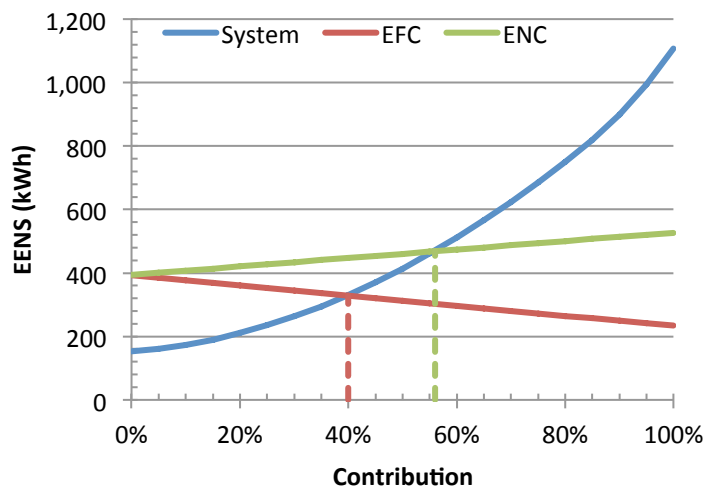


Figure 37: Illustrative example for EFC and ENC

Figure 37 illustrates an example of EFC and ENC contribution estimations. The X-axis represents the contribution, whilst the Y-axis shows the EENS. The system curve shows the relationship between the contribution and the EENS for the system on the left in Figure 35. The EFC and ENC curves show the relationship between EENS and contributions for the two systems on the right of Figure 36. The relevant contribution is found where these curves cross, as denoted by the dashed lines.

#### 4.5 Contribution to Security of Supply if Units Cannot Run in Islanding Mode

To illustrate contribution to security of supply if units cannot run in islanding mode, an example system shown in Figure 38 is used. Group demand is supplied by two circuits<sup>7</sup> of capacity T and three DSR facilities of capacity G. Assuming that a circuit outage is the critical condition (i.e. the rating of one circuit is greater than the total capacity of all units) then the Group Demand which can be supplied by the example system is:  $GD = T + 3FG$ , where F is the contribution factor of DSR facilities.

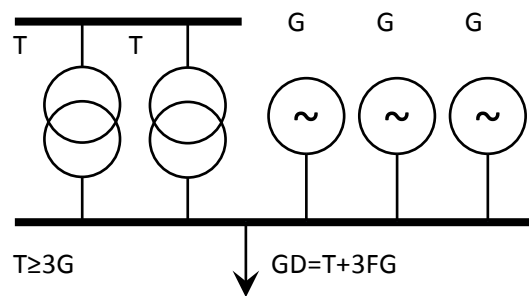


Figure 38: Example system. T – transformer rating, G – DSR capacity, GD – Group Demand, F – contribution factor for DSR

The capacity outage probability table for two circuits is shown in Table 5 whilst the compliance probability table for three DSR facilities is shown in Table 6. The values C and P are state capacity and state probability respectively. P<sub>tn</sub> and P<sub>gn</sub> denote circuits and DSR facilities state probabilities, respectively for state n. A<sub>t</sub> and A<sub>g</sub> denotes circuit and DSR facility availability, respectively, which is calculated as in the following general equation

$$A = \frac{1}{1 + \lambda \cdot MTTR}$$

where  $\lambda$  is an asset failure rate and MTTR is mean time to repair/restoration.

Table 5: Capacity outage probability table for two circuits. Note: \* denotes convolution.

| State | Description   | Capacity (C) | State probability (P) | Value of state probability                                   |
|-------|---------------|--------------|-----------------------|--------------------------------------------------------------|
| 1     | <b>Intact</b> | 2T           | P <sub>t1</sub>       | P <sub>t1</sub> = 1 - P <sub>t2</sub> - P <sub>t3</sub>      |
| 2     | <b>N-1</b>    | T            | P <sub>t2</sub>       | P <sub>t2</sub> = 2 x A <sub>t</sub> x (1 - A <sub>t</sub> ) |
| 3     | <b>N-2</b>    | 0            | P <sub>t3</sub>       | P <sub>t3</sub> = (1 - A <sub>t</sub> ) <sup>2</sup>         |

Table 6: Compliance probability table for three DSR facilities

| State | Description | Capacity | State | Value of state probability |
|-------|-------------|----------|-------|----------------------------|
|-------|-------------|----------|-------|----------------------------|

<sup>7</sup> Generalised circuits are assumed which can consist of transformers, lines or both with overall critical capacity. For illustration only transformers are shown.

|   |                                                | (C) | probability<br>(P) |                                       |
|---|------------------------------------------------|-----|--------------------|---------------------------------------|
| 1 | <b>All sites fully compliant with contract</b> | 3G  | Pg1                | $Pg1 = 1 - Pg2 - Pg3 - Pg4$           |
| 2 | <b>One failure to comply</b>                   | 2G  | Pg2                | $Pg2 = 3 \times Ag \times (1 - Ag)^2$ |
| 3 | <b>Two failures to comply</b>                  | G   | Pg3                | $Pg3 = 3 \times Ag^2 \times (1 - Ag)$ |
| 4 | <b>All fail to respond</b>                     | 0   | Pg4                | $Pg4 = (1 - Ag)^3$                    |

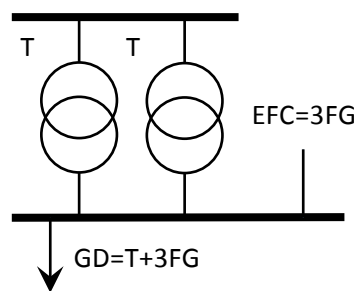
At first sight from Table 5 and Table 6, we might imagine there are a total of  $3 \times 4 = 12$  states of the system. In practice, in the intact state, demand side response would not be called upon, so that only the intact state and  $2 \times 4$  other states exist, totalling 9 states. However, four of these states occur in the N-2 case, in which the generators must run in an islanded state. If they cannot run in an islanded state, then the system has a total of  $1 + 1 \times 4 + 1 = 6$  states including the intact state, all variations of the N-1 state, and the N-2 state.

The capacity probability table shown in Table 7 is obtained by convolution of these two tables and assuming that the DSR facilities cannot run in islanding mode. The Energy Not Supplied (ENS) is shown and E1, E2 and E3 ( $E1 \leq E2 \leq E3$ ) are unsupplied annual energy when capacities of T+2G, T+G and T respectively are superimposed on the LDC. Depending on the contribution factor E1, E2 or E3 might be zero. If the contribution factor is zero then all three (E1, E2 and E3) are zeros. E denotes the total annual energy demand. Given that Group Demand is a function of contribution, then E1, E2, E3, and E are functions of contribution factor F. Multiplying the ENS by the state probability and summing for all states gives the EENS.

**Table 7: Combined capacity probability table for two circuits and three DSR facilities if DSR facilities cannot run in islanded mode; expected energy not supplied if Group Demand is  $GD = T + 3FG$**

| C    | P       | ENS | EENS       |
|------|---------|-----|------------|
| 2T   | Pt1     | 0   | 0          |
| T+3G | Pt2 Pg1 | 0   | 0          |
| T+2G | Pt2 Pg2 | E1  | E1 Pt2 Pg2 |
| T+G  | Pt2 Pg3 | E2  | E2 Pt2 Pg3 |
| T    | Pt2 Pg4 | E3  | E3 Pt2 Pg4 |
| 0    | Pt3     | E   | E Pt3      |

Figure 39 shows a system in which three DSR facilities are replaced by the equivalent firm capacity, equal to  $EFC = 3FG$ , where F is the contribution factor and G is the capacity of a single DSR facility.



**Figure 39: Equivalent system to the one shown in Figure 37 where three DSR facilities are replaced by firm capacity which never fails. T – transformer rating, GD – Group Demand, G – capacity of one DSR facility, F – contribution factor, EFC – Equivalent Firm Capacity**

Table 8 shows the capacity probability table assuming that the equivalent firm capacity cannot remain connected to the network during islanding operation. ENS and EENS are also shown.

**Table 8: Capacity probability table for the system shown in Figure 38 if the equivalent Firm Capacity cannot supply demand in islanding mode**

| C     | P   | ENS | EENS  |
|-------|-----|-----|-------|
| 2T    | Pt1 | 0   | 0     |
| T+3FG | Pt2 | 0   | 0     |
| 0     | Pt3 | E   | E Pt3 |

The EENS is the sum of the individual EENS's in each state. The task is to find F such that the sum of all EENS's in Table 7 is equal to the sum of all EENS's in Table 8. Comparing the EENS shown in Table 7 and Table 8 it can be seen that they are the same only if E1, E2 and E3 are zeros, given that the N-2 term (E Pt3) is equal in both Tables. This is only true if the contribution factor is zero. It should be noted that the conclusion is only valid for networks supplied by two circuits. This is illustrated by a numerical example in Figure 40. This also applies for the ENC approach as the EFC and ENC approaches are practically identical for two circuits if DSR facilities cannot run in islanding mode.

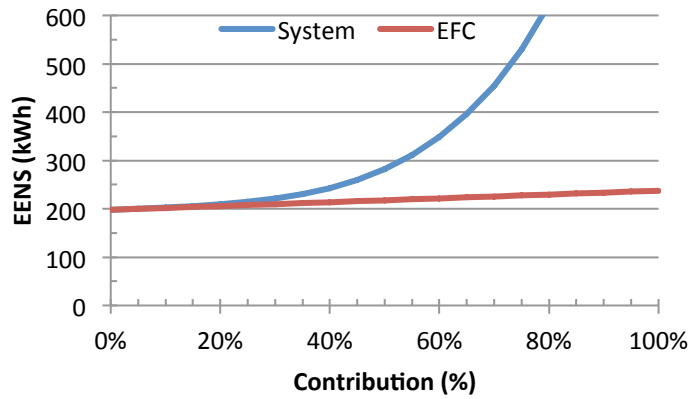


Figure 40: Illustration of the estimation of contribution in network supplied from two circuits if DSR facilities cannot run in the islanding mode

For the ELCC approach the EENS is compared with the situation if the adequate Group Demand,  $GD' = T$ , is supplied by two circuits only. Table 9 shows the capacity outage probability table for this case. Given that the  $GD'$  is less than or equal to  $GD$  in Figure 37, then  $E'$  is less than or equal to  $E$  in Table 7. Hence the same conclusion is valid: EENS values are only the same if the contribution factor is zero, in which case  $GD' = GD$ ,  $E' = E$  and  $E1 = E2 = E3 = 0$ .

Table 9: Capacity outage probability table for two circuits and expected energy not supplied if Group Demand is  $GD' = T$

| C  | P   | ENS  | EENS     |
|----|-----|------|----------|
| 2T | Pt1 | 0    | 0        |
| T  | Pt2 | 0    | 0        |
| 0  | Pt3 | $E'$ | $E' Pt3$ |

It should be noted that it is assumed that demand-led DSR is implicitly delivered under islanding mode.

#### 4.6 Illustration of reliability performance as delivered by DSR compared with network reinforcement

In this section, each of the methods for determining the capacity credit of DSR facilities are compared with the network needed to ensure compliance to the security standard. The methods are: (i) P2/6 - Equivalent Circuit Capacity' (ECC), (ii) Effective Load Carrying Capability (ELCC), (iii) Equivalent Firm Capacity (EFC) and (iv) Equivalent Network Capacity (ENC). The approach is illustrated in Figure 41.

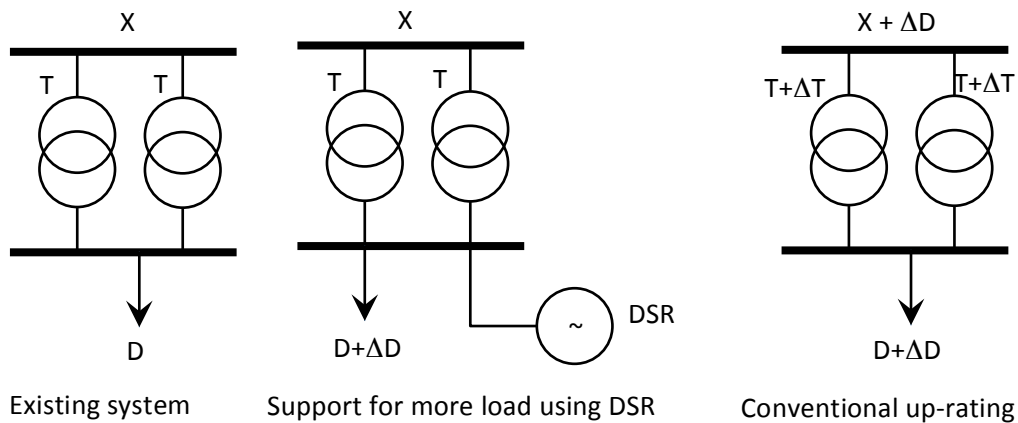


Figure 41: Illustration of the approach for comparison of different methods for measuring the capacity credit of DSR facilities. Generalised circuits consisting of transformers, lines or both are assumed. For simplicity, only transformers are shown

A network (capacity  $X$ ) and a DSR facility that supply Group Demand ( $D+\Delta D$ ) are considered. Each of the capacity credit methodologies calculates different values of  $\Delta D$ . The key task is to compare the reliability performance delivered by DSR (with different capacity credits derived by alternative methods) with network reinforcement.

For illustration, two transformer circuits are considered with each circuit rating of 15 MVA. Different reliability of circuits is considered assuming failure rate of 2%, 10% and 20% occurrences per year (which is equivalent to one failure on average, every 50, 10 or 5 years respectively) with mean time to repair (MTTR) of 24 and 240 hours (i.e. expected duration of outage 1 day or 10 days).

#### 4.6.1 Example with three DSR facilities

Table 10 shows the results of an example with different reliability measures of circuit mean time to repair and circuit failure rate and different capacity credit methods. The group demand increase achieved with the DSR facility is shown, as calculated by each of the methods.

In each case, the group demand increase could have been equally achieved with a conventional replacement of both transformers with transformers with a rating equal to  $D+\Delta D$ . Importantly the two columns under Expected Energy Not Served (EENS) quantify the energy at risk in the two cases, of using the DSR facility and using the conventional up-rating approach. The EENS is calculated as the sum of expectations of energy not supplied across all system states. The expectation of energy not supplied for one state is calculated by multiplying the area under the load duration curve and above the state capacity with state probability. This includes all potential combinations of intact system, N-1, N-2, and etc. The LDC is obtained by using an average LDC shape and scaling it to match the Group Demand. For visual analysis various figures are shown below.

Table 10: Results for an example with three DSR facilities

| Circuit<br>MTTR (h) | Circuit failure<br>rate (%) | Method | Contribution | $\Delta D$<br>(GD increase MW) | EENS (kWh) |                           |
|---------------------|-----------------------------|--------|--------------|--------------------------------|------------|---------------------------|
|                     |                             |        |              |                                | Using DSR  | Conventional<br>up-rating |
| 24                  | 2%                          | P2/6   | 60.0%        | 1.80                           | 5.40       | 0.36                      |
|                     |                             | ELCC   | 11.9%        | 0.36                           | 0.32       | 0.33                      |
|                     |                             | EFC    | 11.7%        | 0.35                           | 0.32       | 0.33                      |
|                     |                             | ENC    | 12.6%        | 0.38                           | 0.33       | 0.33                      |
|                     | 10%                         | P2/6   | 60.0%        | 1.80                           | 33.10      | 8.89                      |
|                     |                             | ELCC   | 20.9%        | 0.63                           | 7.94       | 8.27                      |
|                     |                             | EFC    | 20.4%        | 0.61                           | 7.86       | 8.26                      |
|                     |                             | ENC    | 23.5%        | 0.71                           | 8.31       | 8.31                      |
|                     | 20%                         | P2/6   | 60.0%        | 1.80                           | 81.43      | 35.54                     |
|                     |                             | ELCC   | 26.2%        | 0.79                           | 31.73      | 33.39                     |
|                     |                             | EFC    | 25.3%        | 0.76                           | 31.35      | 33.33                     |
|                     |                             | ENC    | 30.4%        | 0.91                           | 33.66      | 33.66                     |
| 240                 | 2%                          | P2/6   | 60.0%        | 1.80                           | 81.43      | 35.54                     |
|                     |                             | ELCC   | 26.2%        | 0.79                           | 31.73      | 33.39                     |
|                     |                             | EFC    | 25.3%        | 0.76                           | 31.35      | 33.33                     |
|                     |                             | ENC    | 30.4%        | 0.91                           | 33.66      | 33.66                     |
|                     | 10%                         | P2/6   | 60.0%        | 1.80                           | 1,012.95   | 884.55                    |
|                     |                             | ELCC   | 40.8%        | 1.22                           | 789.76     | 854.14                    |
|                     |                             | EFC    | 38.5%        | 1.15                           | 775.26     | 850.51                    |
|                     |                             | ENC    | 49.7%        | 1.49                           | 868.26     | 868.26                    |
|                     | 20%                         | P2/6   | 60.0%        | 1.80                           | 3,525.59   | 3,518.94                  |
|                     |                             | ELCC   | 47.0%        | 1.41                           | 3,141.85   | 3,437.22                  |
|                     |                             | EFC    | 43.8%        | 1.31                           | 3,076.12   | 3,417.28                  |
|                     |                             | ENC    | 59.8%        | 1.79                           | 3,517.61   | 3,517.61                  |

As expected, in highly reliable networks (characterised with low circuit failure rates and short repair/restoration times) the ELCC, EFC and ENC methods allocate a much lower contribution to DSR if that same high reliability is to be maintained and hence would result in a lower increase of Group Demand when compared with P2/6. In practice however, this reliability may already be well in excess of P2/6 requirements due to the other incentives, which are in place in the GB regulatory environment, in particular the Interruption Incentive Scheme. The ENC and P2/6 methods produce similar contributions in networks with low reliability (failure rate 20% and MTTR of 240 hours).

It is important to note that the EENS associated with P2/6 approach to determining capacity contribution of DSR is significantly higher when compared with EFC, ENC and ELCC approaches, particularly in highly reliable networks. Furthermore, EENS when DSR is used to substitute for network reinforcement is very similar to the EENS in case of idealised conventional up-rating, when EFC, ENC and ELCC approaches are used<sup>8</sup>. This is in stark contrast to P2/6 approach, as the EENS is very significant in

<sup>8</sup> Note that in case of ENC, driven by its very definition, the EENS when DSR is used to substitute for network reinforcement is exactly equal to the EENS in case of idealised conventional up-rating.



cases when DSR is used to provide security of supply, in comparison to the EENS associated with conventional up-rating of the network. This difference diminishes in networks characterised with low reliability.

As it will be demonstrated in section 5.3, in case of P2/6 approach, a significant part of the EENS is driven by the N-1 condition, while in the EFC, ENC and ELCC based methods the EENS is dominated by the N-2 condition.

Figure 42 shows the Group Demand increase for different capacity credit methods and different circuit reliability parameters. It can be seen that the contribution allocated to DSR by the present security standard P2/6 is, by definition, independent of network reliability performance and is generally higher when compared with other methods. We also observe that the capacity contribution allocated by other methods is, in broad terms, similar, and increases when network reliability performance reduces. The EFC method has the smallest Group Demand increase, followed by the ELCC method with the ENC method having the largest increase. The group demand increase is the same as the contribution in (MW).

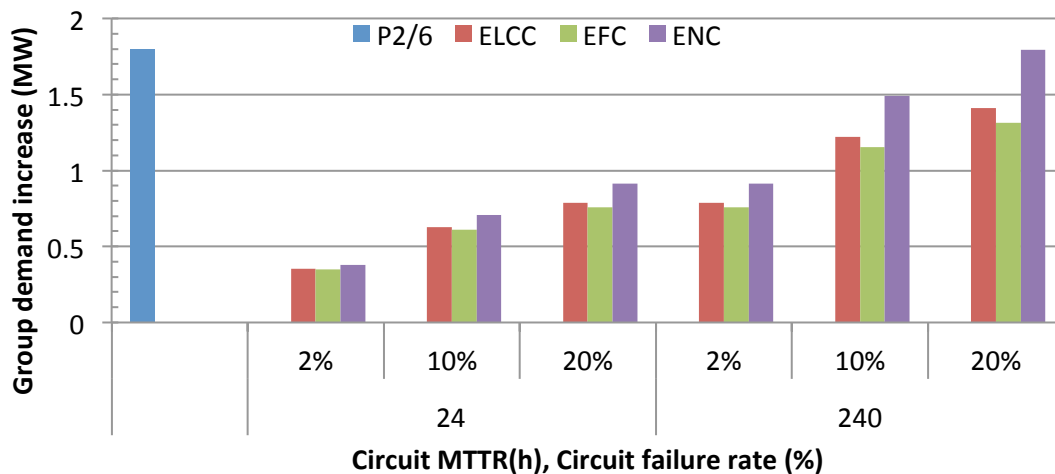


Figure 42: Group Demand Increase ( $\Delta D$ ) as calculated by different methods

Figure 43 shows the contribution in (%) and probability of DSR facilities actually delivering the corresponding contribution. The contribution percentage follows the same pattern as the Group Demand increase and the conclusions are the same. It can be seen that the probability of delivering a given contribution is higher for smaller contributions. In this context, the probability of delivery of a given contribution allocated by P2/6 is the lowest in this example. It should be noted that even though the contribution of DSRs is calculated in network setting the probability of delivery of a contribution depends only on DSRs states and probabilities.

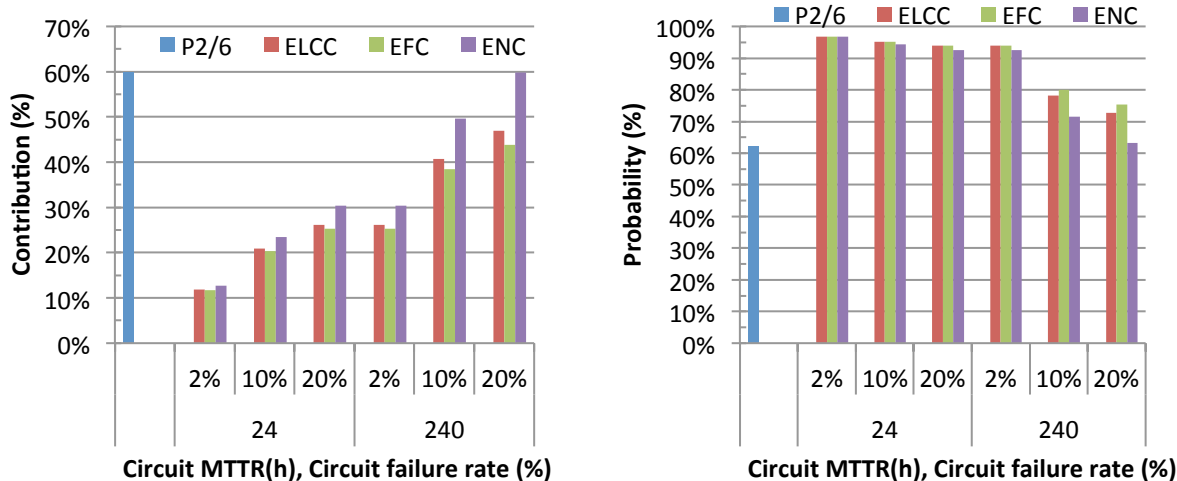


Figure 43: Contribution (%) (left) and probability of delivering contribution (right)

Figure 44 compares reliability performance delivered by DSR with network reinforcement. It can be seen that the EENS is much higher for the P2/6 capacity credit method in networks with high circuit reliability. In the case of a circuit failure rate of 2% and MTTR of 24 hours the EENS is more than 15 times larger than it is for the ENC method. In networks with lower circuit reliability the difference diminishes. It should be noted that contracted demand if not reduced is counted in EENS. However, in Capacity for Customers project [42] DSR comes from customers who are willing to be restored last, and sit behind a dedicated circuit breaker. This introduces a distinction between energy not served and energy not served but pre-agreed to be at risk, therefore not counting towards the EENS figure.

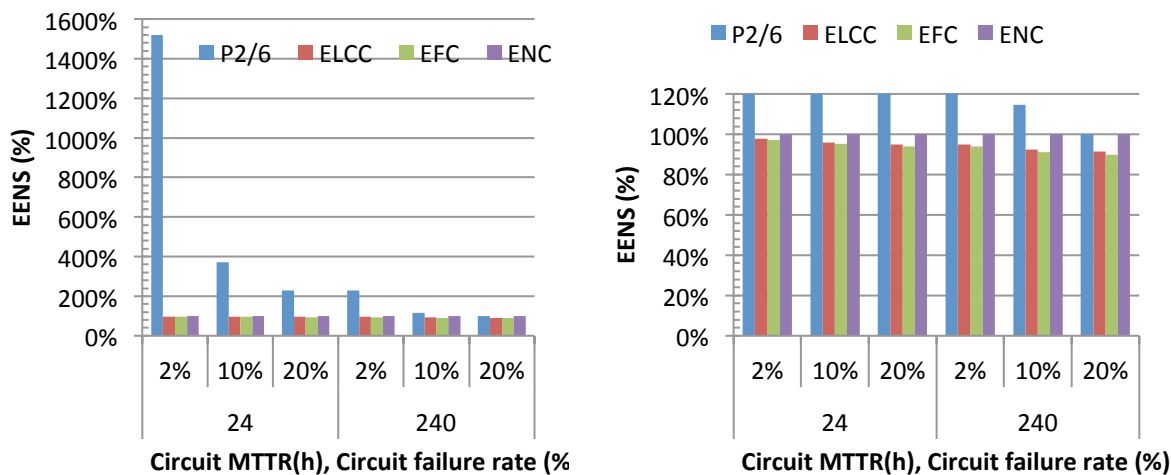


Figure 44: Comparing Expected Energy Not Supplied (EENS) delivered by DSR and network reinforcement delivered capacity (right: zoom); Note that the ENC method based capacity contribution evaluation delivers the same EENS as the network reinforcement (100% agreement).

#### 4.6.2 Example with six DSR facilities

Table 11 shows the results of an example with different circuit reliability measures of circuit MTTR and circuit failure rate, and different capacity credit methods. The group demand increase achieved with the DSR facility is shown, as calculated by each of the methods.

In each case, the group demand increase could have been equally achieved with a conventional replacement of both transformers with transformers with a rating equal to  $D+\Delta D$ . Importantly the two columns under Expected Energy Not Served (EENS) quantify the energy at risk in the two cases, of using the DSR facility and using the conventional up-rating approach. For visual analysis, various figures are shown below.

Table 11: Results for an example with six DSR facilities

| Circuit MTTR (h) | Circuit failure rate (%) | Method | Contribution | $\Delta D$ (GD increase MW) | EENS (kWh) |                        |
|------------------|--------------------------|--------|--------------|-----------------------------|------------|------------------------|
|                  |                          |        |              |                             | Using DSR  | Conventional up-rating |
| 24               | 2%                       | P2/6   | 62.1%        | 3.73                        | 10.94      | 0.40                   |
|                  |                          | ELCC   | 24.0%        | 1.44                        | 0.32       | 0.35                   |
|                  |                          | EFC    | 23.5%        | 1.41                        | 0.31       | 0.35                   |
|                  |                          | ENC    | 25.9%        | 1.55                        | 0.35       | 0.35                   |
|                  | 10%                      | P2/6   | 62.1%        | 3.73                        | 60.60      | 9.91                   |
|                  |                          | ELCC   | 32.3%        | 1.94                        | 7.94       | 8.96                   |
|                  |                          | EFC    | 31.4%        | 1.88                        | 7.70       | 8.93                   |
|                  |                          | ENC    | 35.9%        | 2.15                        | 9.08       | 9.08                   |
|                  | 20%                      | P2/6   | 62.1%        | 3.73                        | 135.91     | 39.61                  |
|                  |                          | ELCC   | 36.4%        | 2.19                        | 31.73      | 36.35                  |
|                  |                          | EFC    | 35.2%        | 2.11                        | 30.66      | 36.19                  |
|                  |                          | ENC    | 40.9%        | 2.45                        | 36.92      | 36.92                  |
| 240              | 2%                       | P2/6   | 62.1%        | 3.73                        | 135.91     | 39.61                  |
|                  |                          | ELCC   | 36.4%        | 2.19                        | 31.73      | 36.35                  |
|                  |                          | EFC    | 35.2%        | 2.11                        | 30.66      | 36.19                  |
|                  |                          | ENC    | 40.9%        | 2.45                        | 36.92      | 36.92                  |
|                  | 10%                      | P2/6   | 62.1%        | 3.73                        | 1,265.32   | 986.03                 |
|                  |                          | ELCC   | 46.6%        | 2.79                        | 789.76     | 936.84                 |
|                  |                          | EFC    | 44.2%        | 2.65                        | 756.44     | 929.38                 |
|                  |                          | ENC    | 54.5%        | 3.27                        | 962.08     | 962.08                 |
|                  | 20%                      | P2/6   | 62.1%        | 3.73                        | 3,980.68   | 3,922.65               |
|                  |                          | ELCC   | 51.3%        | 3.08                        | 3,141.84   | 3,786.32               |
|                  |                          | EFC    | 48.1%        | 2.89                        | 2,997.55   | 3,746.54               |
|                  |                          | ENC    | 61.5%        | 3.69                        | 3,914.98   | 3,914.99               |

As indicated, in highly reliable networks the application of ELCC, EFC and ENC methods results in lower increase in Group Demand when compared with EN P2/6, while in networks characterised with low reliability these differences are much smaller. Consequently, the EENS obtained in the P2/6 case is significantly higher when compared with the EENS associated with EFC, ENC and ELCC approaches, particularly in highly reliable networks. In contrast to P2/6 approach, EFC, ENC and ELCC approaches, give very similar EENS in both cases, when DSR is used to substitute for network reinforcement and

when idealised conventional up-rating is used. These differences diminish in networks characterised with low reliability.

This is also presented in Figure 45 that shows Group Demand increase for different capacity credit methods and different circuit reliability parameters. As in the example with three DSR facilities, in networks characterised with high reliability P2/6 based approach suggests significantly larger Group Demand increase in comparison with the other three approaches. However, the suggested increase in Group Demand by P2/6 and the ENC method are similar in networks with low reliability circuits (failure rate is 20% and MTTR is 240 hours).

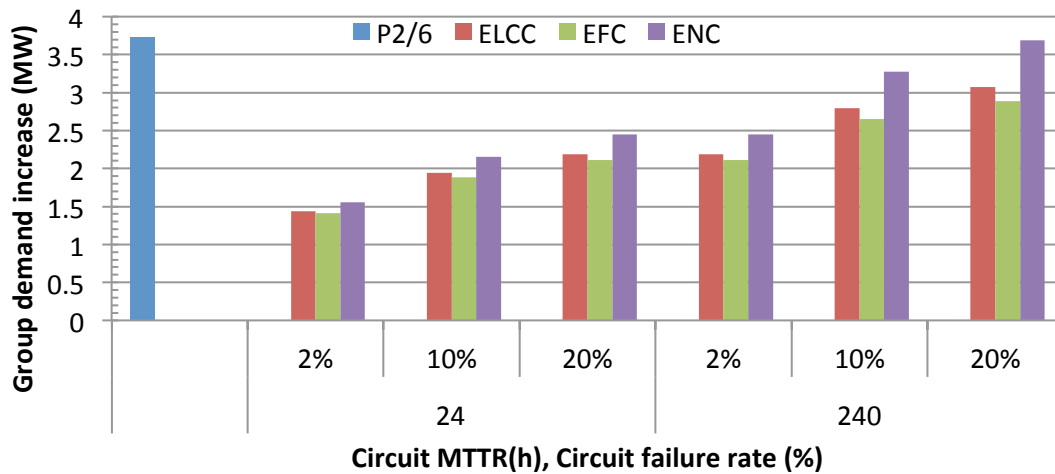


Figure 45: Group Demand Increase (ΔD) as calculated by different methods

Figure 46 shows the contribution (%) and the probability of DSR facilities delivering the corresponding contribution. The contribution percentage follows the same pattern as Group Demand increase and the conclusions are the same. It can be seen that the probability of delivering a given contribution is higher for smaller contributions. The method described in P2/6 results in the smallest probability in this example.

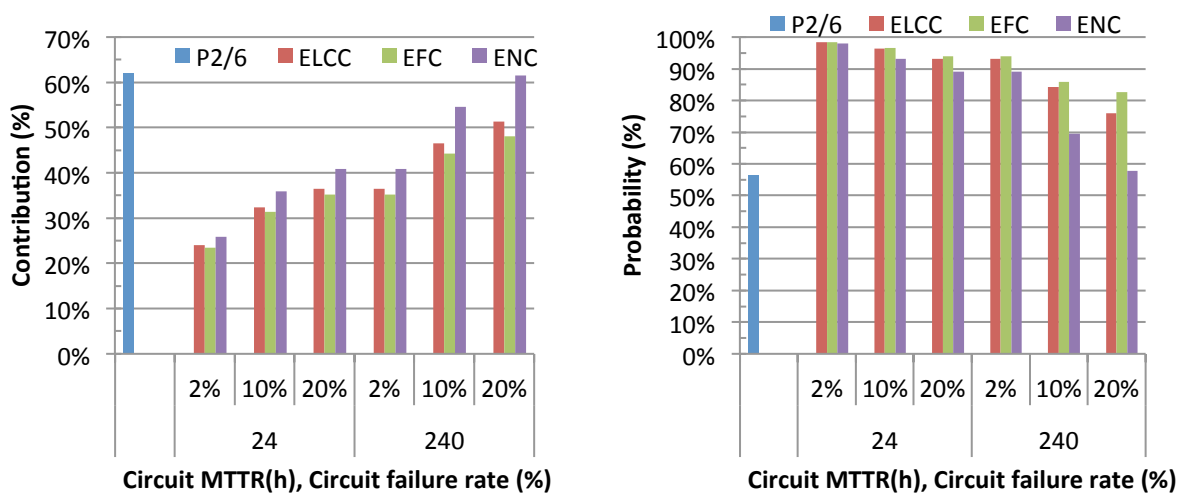


Figure 46: Contribution (%) (left) and probability of delivering contribution (right)

Figure 47 compares the reliability performance delivered by DSR with network reinforcement. It can be seen that the EENS is much higher for the P2/6 capacity credit method in networks with high circuit

reliability and in case of a circuit failure rate of 2% and MTTR of 24 hours, the EENS is more than 15 times that of the ENC method. In networks with lower circuit reliability the difference diminishes.

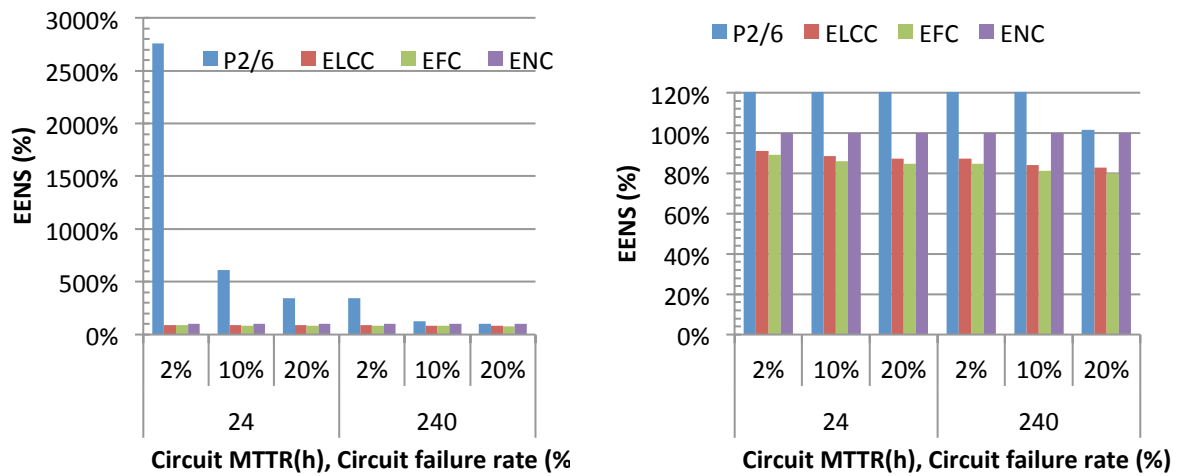


Figure 47: Comparing Expected Energy Not Supplied delivered by DSR and network reinforcement delivered capacity (right: zoom). Note that the ENC method based on evaluation of capacity contribution delivers the same EENS as network reinforcement (100% agreement).

The P2/6 contribution (%) of six DSR facilities is slightly greater than for three facilities. However, the ELCC, EFC and ENC contributions (%) of six DSR facilities are about twice that of three DSR facilities in networks with higher reliability of circuits. In networks with a lower reliability of circuits the difference is reduced. Note that the performance of the network with DSR and capacity contribution allocated using the ENC method coincides with the performance of an equivalent network with reinforcement, as the definition of the method requires.

## 5 Quantifying the security contribution of generation and demand led DSR trialled in Low Carbon London

### 5.1 Contribution of different DSR technologies

For illustration, networks with two and four supply circuits are considered. The rating of each circuit is 15 MVA. Different reliabilities of circuits are considered assuming failure rates of 2% and 10% per year and a mean time to repair (MTTR) of 24 and 240 hours. This implies that the availability of a circuit is in the range 99.73% to 99.995%.

All DSR facilities of the same type are considered and the total ratings are: for diesel 6 MW, CHP 6.695 MW and demand reduction 3.3 MW, as shown in Table 4. The aggregated state probabilities, shown in Figure 26 to Figure 28, respectively, are used and the average LDC shown in Figure 30 is also used.

The contribution to security of supply for different approaches for diesel is shown in Figure 48. The X-axis represents (from bottom) the number of circuits, circuit MTTR and circuit failure rate, while the Y-axis represents contribution to security of supply.

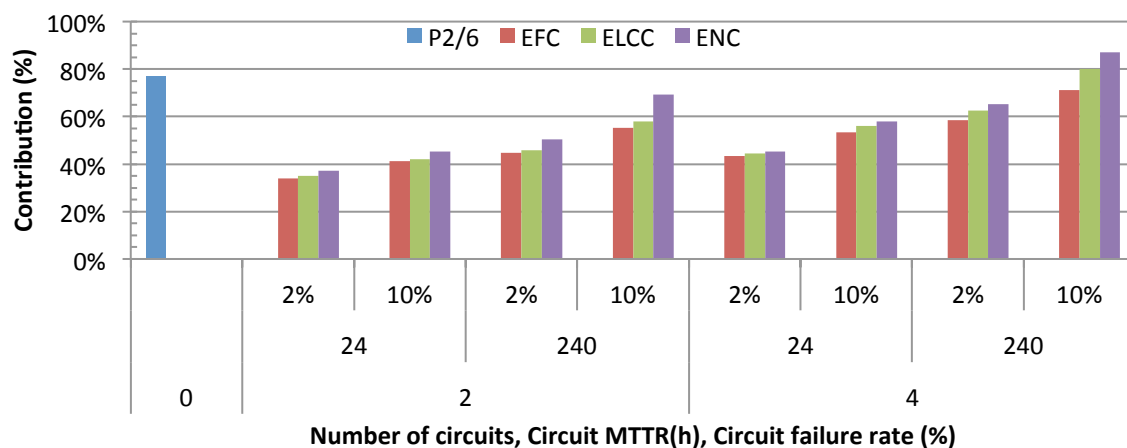


Figure 48: Contribution to security of supply of aggregated diesel facilities with different approaches and different circuit parameters

The contribution as calculated in the present security of supply standard, ER P2/6, does not depend on network parameters: in this example it is 77%. The contribution calculated by other approaches include network parameters and it can be seen that the higher the circuit reliability, the lower the contribution and vice versa. The smallest contribution is obtained for the EFC approach while the highest for the ENC approach. The ELCC approach gives contributions between these two approaches. It can be seen that, in general, the P2/6 approach overestimates the contribution and if circuits are reliable this overestimation is significant.

Figure 49 and Figure 50 show the contribution to security of supply of aggregated CHP and demand-led DSR facilities, respectively.

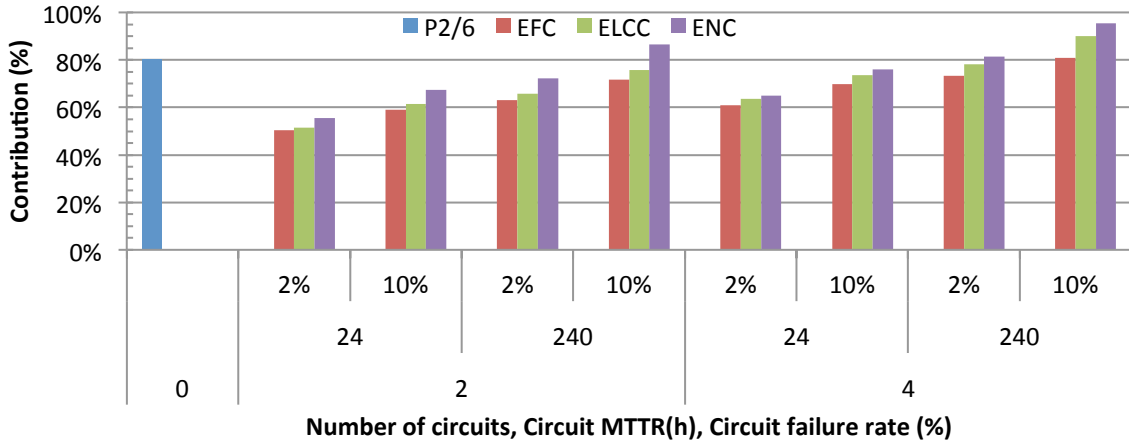


Figure 49: Contribution to security of supply of aggregated CHP facilities by different approaches and for different circuit parameters

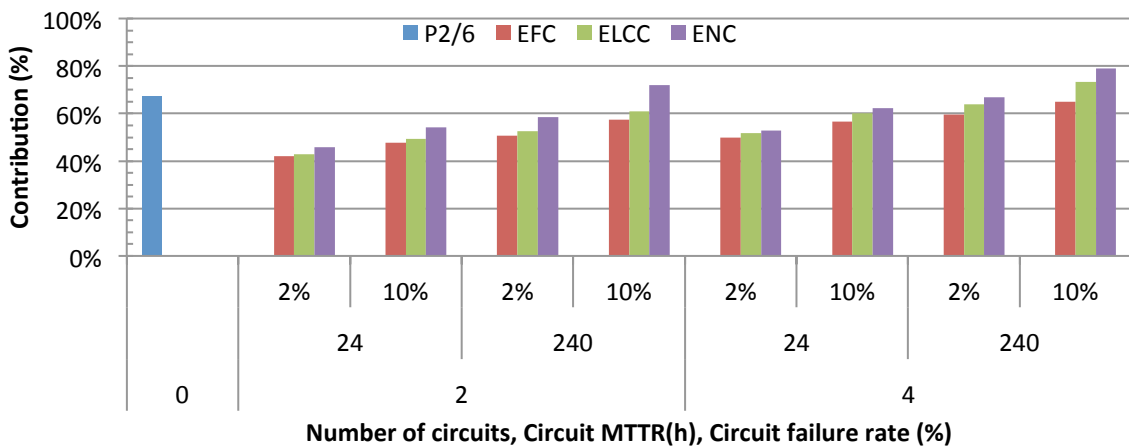


Figure 50: Contribution to security of supply of aggregated demand-led DSR facilities by different approaches and for different circuit parameters

Similar conclusions apply to CHP and demand-led DSR facilities.

## 5.2 Impact of LDC Uncertainty and MTTR Distribution on Contribution

For the network configuration in the section 5.1, the uncertainty in average load duration curve is assumed to be as illustrated in Figure 51. The knee point of the curve is where the calculation of EENS is particularly sensitive. Above the knee point the marginal change of EENS by the change of power is smaller compared with the case below the knee point. The uncertainty, for illustration, is introduced into the knee point: the duration is assumed to have a uniform distribution from 2.5% to 12.5% and power a uniform distribution from 85% to 95%. In addition the uniform distribution of MTTR is assumed to range from 0 to twice the average value.

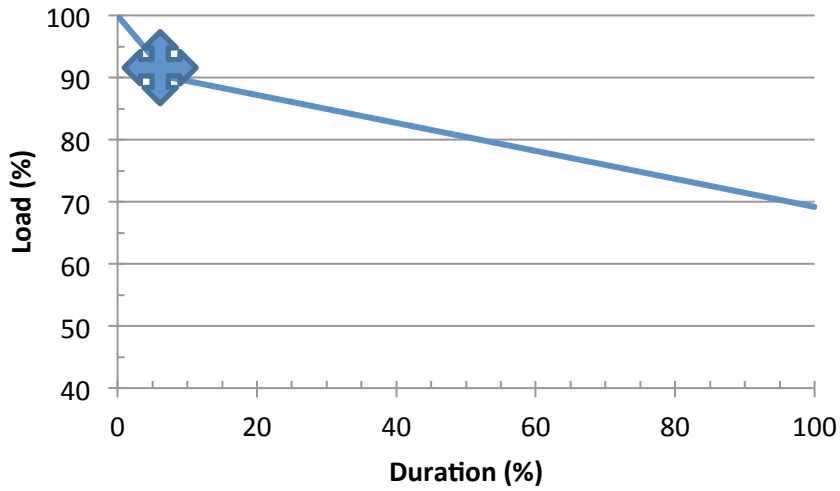


Figure 51: Illustration of average LDC uncertainty

The contribution to security of supply of Diesel, CHP and demand-led DSR facilities are shown in Figure 52 to Figure 54 respectively. The results are shown for the EFC and ENC approaches (note that it is assumed that the results of the ELCC approach would lie between the two).

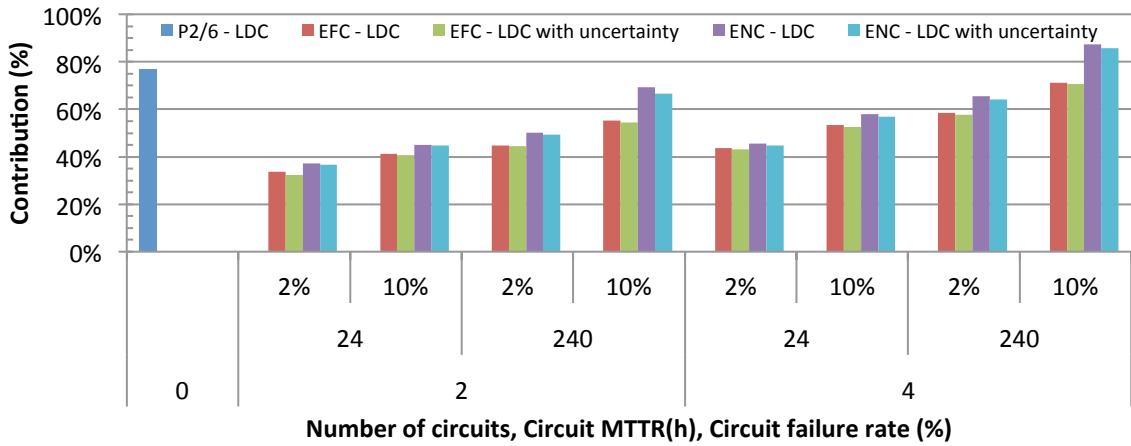


Figure 52: Comparison of the contribution factors for diesel facilities for different approaches, circuit reliability parameters and with and without LDC uncertainty



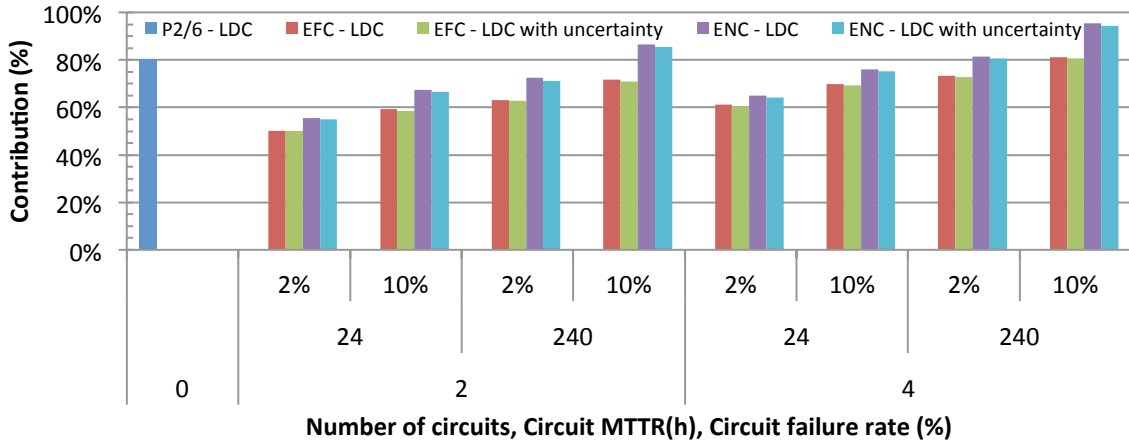


Figure 53: Comparison of the contribution factors for CHP facilities for different approaches, circuit reliability parameters and with and without LDC uncertainty

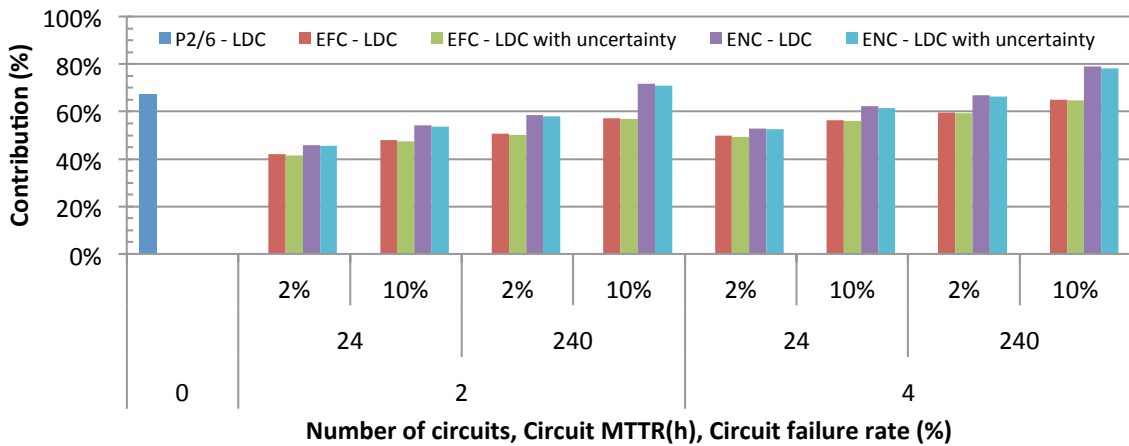


Figure 54: Comparison of the contribution factors for demand-led DSR facilities for different approaches, circuit reliability parameters and with and without LDC uncertainty

It can be seen that the effect of LDC uncertainty and MTTR distribution is relatively small for the particular example analysed, where the contribution to security of supply is slightly lower.

### 5.3 Impact of the Number of DSR Facilities on capacity credit (security contribution)

For illustration, a primary substation with two transformers (circuits) is considered. Each circuit rating is 15 MVA. Different reliabilities of circuits are considered, assuming failure rates of 2%, 10% and 20% (on average, one fault every 50, 10 and 5 years respectively) with mean time to repair (MTTR) of 24 and 240 hours. This implies that the availability of a circuit is in the range 99.73% to 99.995%.

The number of demand-led DSR facilities is varied between 1 and 10, while keeping total demand reduction capacity fixed at 3 MW. The individual state probabilities, shown in Figure 28 (left), are used. Convolution is used to calculate state probabilities for more than one facility and the resulting probabilities for 1, 3, 5 and 10 facilities are shown in Figure 55. The average LDC shown in Figure 30 is used.

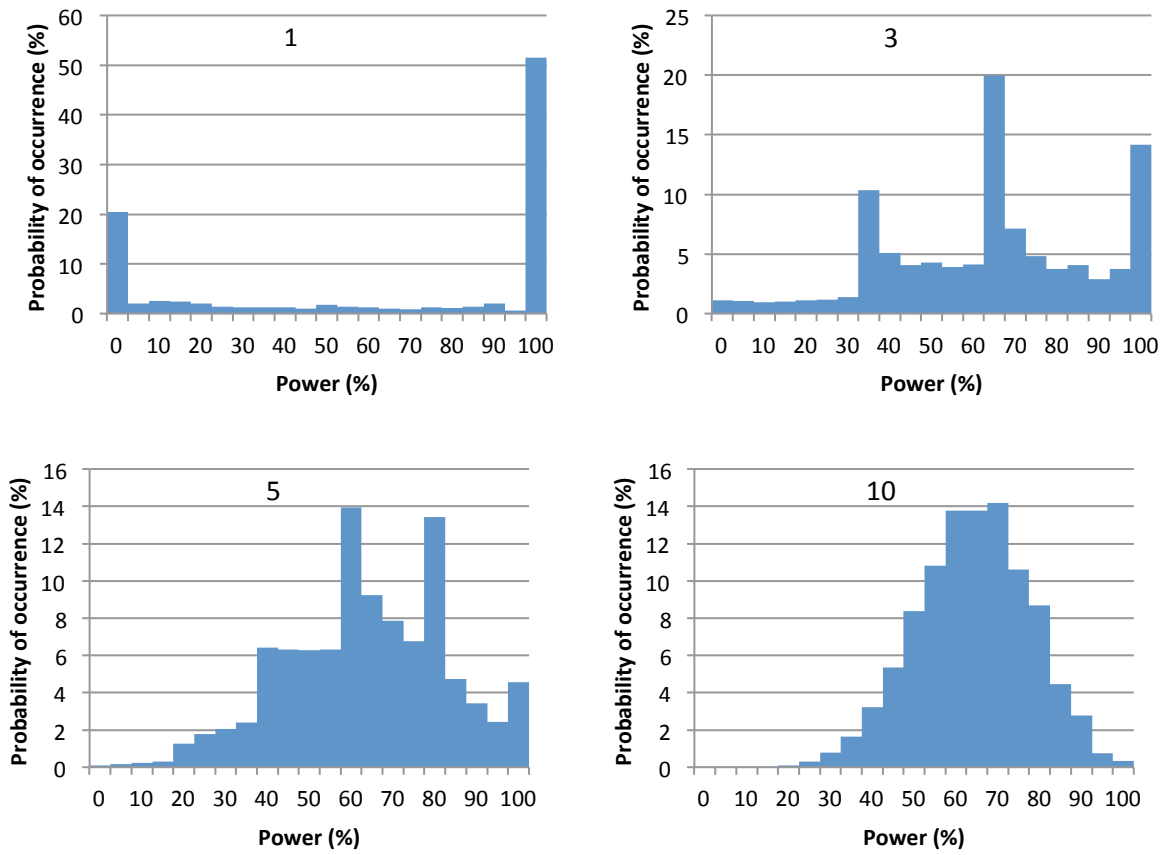


Figure 55: State probabilities for 1, 3 5 and 10 demand-led DSR facilities, respectively. Source (top left chart): [40]

The contribution to security of supply for different approaches is shown in Figure 56. The X-axis represents (from bottom) circuit MTTR, circuit failure rate and the number of demand-led DSR facilities, while the Y-axis represents contribution.

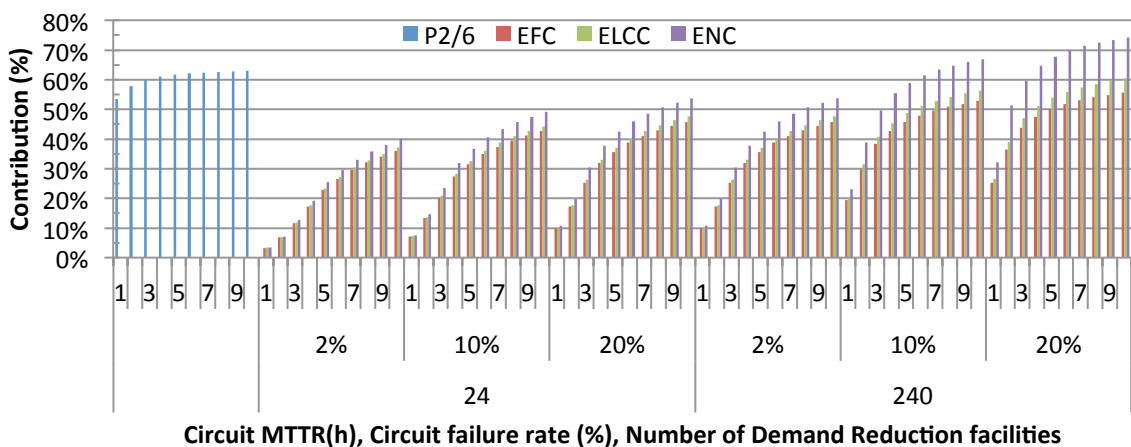


Figure 56: Comparison of contribution factors for different number of demand-led DSR facilities, different approaches and different reliability parameters of circuits

The contribution estimated by P2/6 approach increased with the number of facilities from about 54% to 63%. However, a significant variation of contribution to security of supply with the number of facilities can be observed for the other three approaches, which take network reliability into consideration. As

indicated earlier, we also observe that the level of capacity contribution allocated by methods other than P2/6 is in broad terms similar, and increases when network reliability performance reduces. The EFC method allocates the lowest contribution, followed by the ELCC method and then by the ENC approach (we note that contributions allocated by the ELCC and EFC approaches are very similar). As expected, in highly reliable networks the ELCC, EFC and ENC methods, given their definitions, allocate much lower contributions to DSR when compared with P2/6. The ENC method and P2/6 produce similar contributions in low reliability networks.

Figure 57 shows the probability of DSR actually delivering the contribution that is allocated.

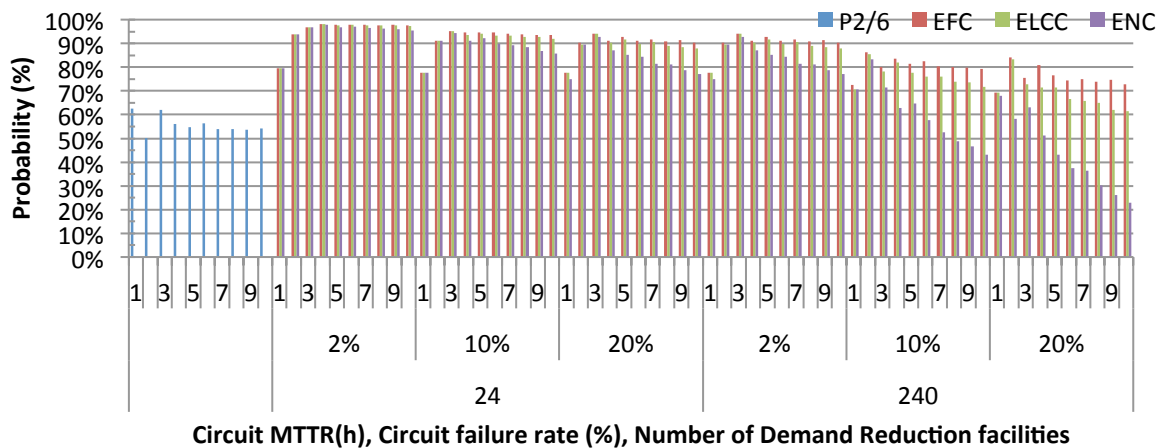


Figure 57: Probability of different numbers of demand response facilities delivering a given contribution

It can be seen that the highest confidence in delivery of contribution is associated with the EFC approach, as the contribution is the smallest. The ENC approach, for systems with low reliability network circuits and for high numbers of demand-led DSR facilities, has the lowest confidence in delivery of contribution. However all three approaches, except in some cases for the ENC approach, result in a higher probability of delivering the allocated contribution than the P2/6 approach.

Table 12 and Figure 58 show the impact on EENS for different approaches for the example of three demand-led DSR facilities of 1 MW each and for two circuits. Here the circuit failure rate is assumed to be 10% while the MTTR is 24 hours for which the P2/6, EFC and ENC contribution factors are 60%, 20% and 24%, respectively. The mean EENS of about 7.8 kWh is smallest for the EFC approach followed closely by the ENC approach and significantly higher (33.1 kWh) for the P2/6 approach. It can be seen that EENS can be significantly higher in a small percentage of cases. For example, for the P2/6 contribution, EENS can be more than 189 kWh in 1% of cases.

Table 12: Impact on EENS

| Cumulative probability (%) | EENS (kWh)      |      |      |
|----------------------------|-----------------|------|------|
|                            | P2/6            | EFC  | ENC  |
| 1.0%                       | 189.5           | 82.9 | 85.8 |
| 5.0%                       | 102.8           | 33.7 | 34.8 |
|                            | Mean EENS (kWh) |      |      |
| 33.3%                      | 33.1            |      |      |
| 23.8%                      |                 | 7.8  |      |
| 24.1%                      |                 |      | 8.3  |

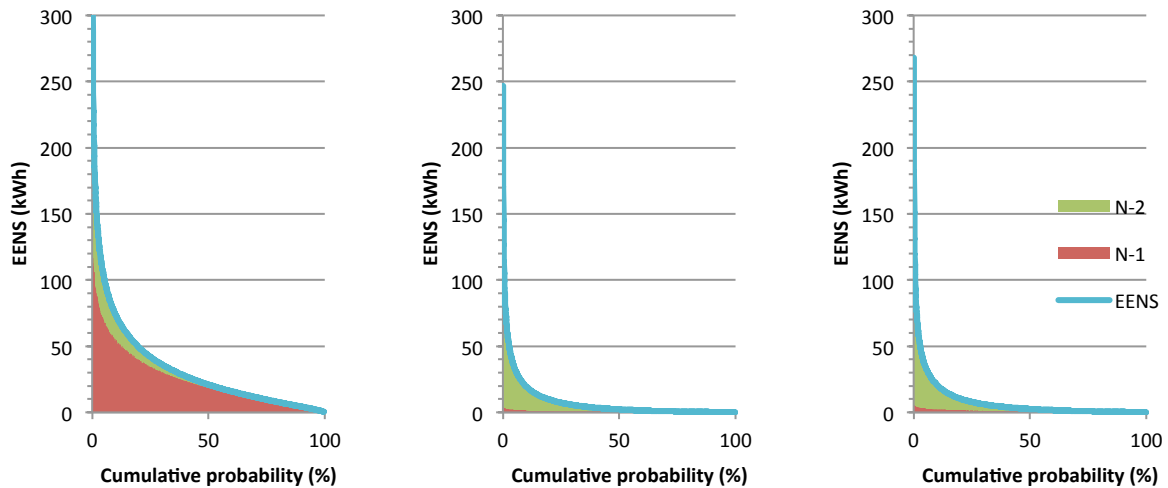


Figure 58: Cumulative probability of EENS if contribution is calculated by P2/6 (left), EFC (middle) and ENC (right) approach; contribution factors are 60%, 20% and 24%, respectively; example is for three demand-led DSR facilities of 1 MW each and circuit failure rate is 10% while MTTR is 24 hours

Furthermore, from Figure 58 it can be seen that in P2/6 approach a significant part of EENS comes from the N-1 condition, while in the EFC and ENC, EENS is dominated by the N-2 condition.

#### 5.4 Contractual Redundancy

One way of increasing the probability of delivering the contribution made by DSR facilities is to introduce redundancy by choosing larger number of contracted facilities. The number of DSR facilities is varied from 3 to 5 while keeping fixed demand reduction capacity of each facility of 0.3 MW. The individual state probabilities, shown in Figure 28 (left), are used. Convolution is used to calculate the state probabilities for more than one facility. The average LDC shown in Figure 30 is used.

Figure 59 shows the contribution calculated by various approaches for three, four and five demand-led DSR facilities and a range of circuit reliability parameters. The P2/6 contribution factor increases from 60% to 62% if the number of demand-led DSR facilities increases from three to five. In other approaches the contribution is much smaller for more reliable circuits, but increases more steeply as the number of demand-led DSR facilities increases.

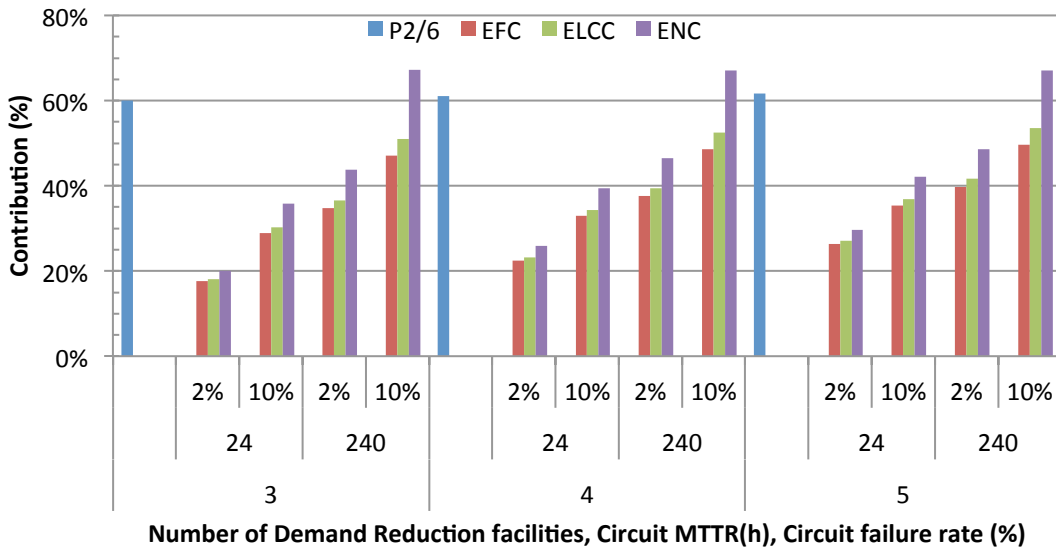


Figure 59: Comparison of contribution factors for different numbers of demand-led DSR facilities and different approaches and circuit reliability parameters

For further comparison, the probabilities of delivering the contributions Figure 59 are shown in Figure 60.

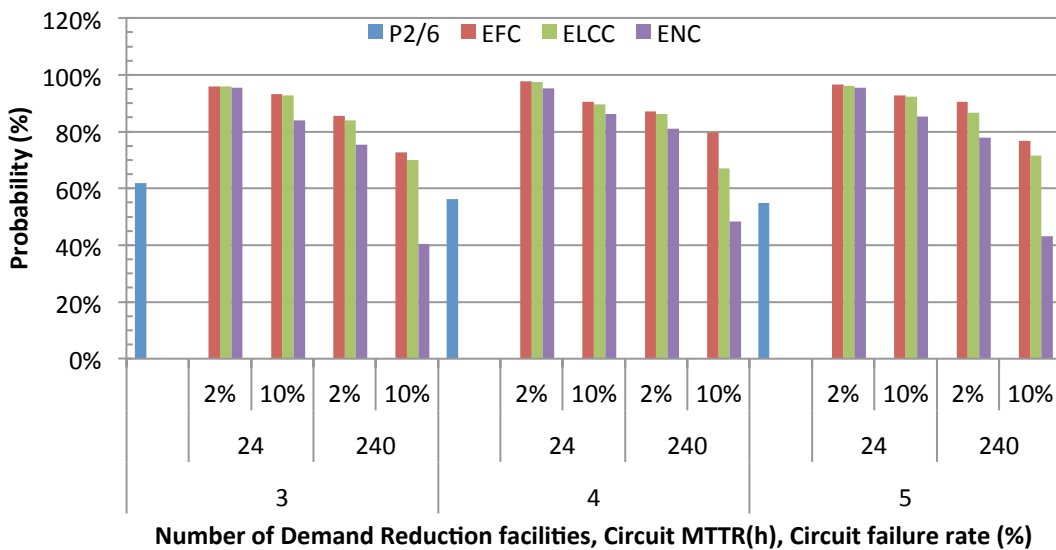


Figure 60: Probability of different number of demand-led DSR facilities delivering contribution for different approaches

The probability of delivering a contribution by assuming a P2/6 contribution factor of 60% for three demand-led DSR facilities but contracting three, four or five facilities is shown in Figure 61.

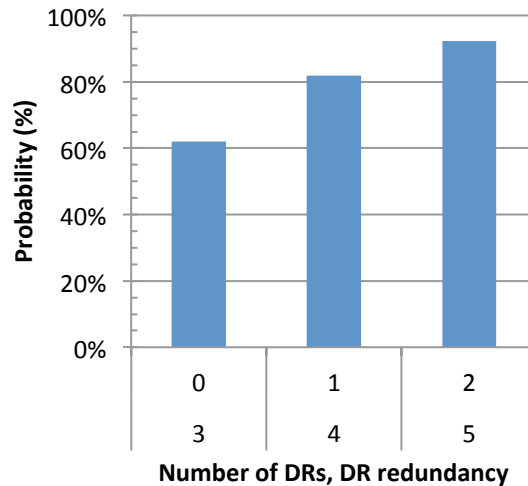


Figure 61: Comparison of probability of demand-led DSR facilities delivering contribution for different redundancies

It can be seen that the probability of set of DSR facilities delivering the P2/6 contribution increases from 62% to 82% for N-1 and to 92% for N-2 DSR redundancy. This is about a 50% increase in probability for contracting two more demand-led DSR facilities.

## 5.5 Coincidence in Delivery and Impact of Materiality

For illustration, two circuits are considered with each circuit having a rating of 15 MVA. Different reliabilities of circuits are considered, assuming failure rates of 2% and 10% per year with mean time to repair (MTTR) of 24 and 240 hours.

Six demand-led DSR facilities, each with DSR capacities of 0.3, 1 and 2 MW, are considered. The individual state probabilities, shown in Figure 28 (left), are used. Convolution is used to calculate the state probabilities for the six facilities assuming different coincidences of delivery of 0%, 10%, 25%, 50% and 100%. The average LDC shown in Figure 30 is used.

The impact of demand-led DSR penetration and coincidence of delivery on contribution to security of supply by different approaches is shown in Figure 62. The X-axis represents (from bottom): coincidence in delivery, circuit MTTR and circuit failure rate. The Y-axis is contribution factor.

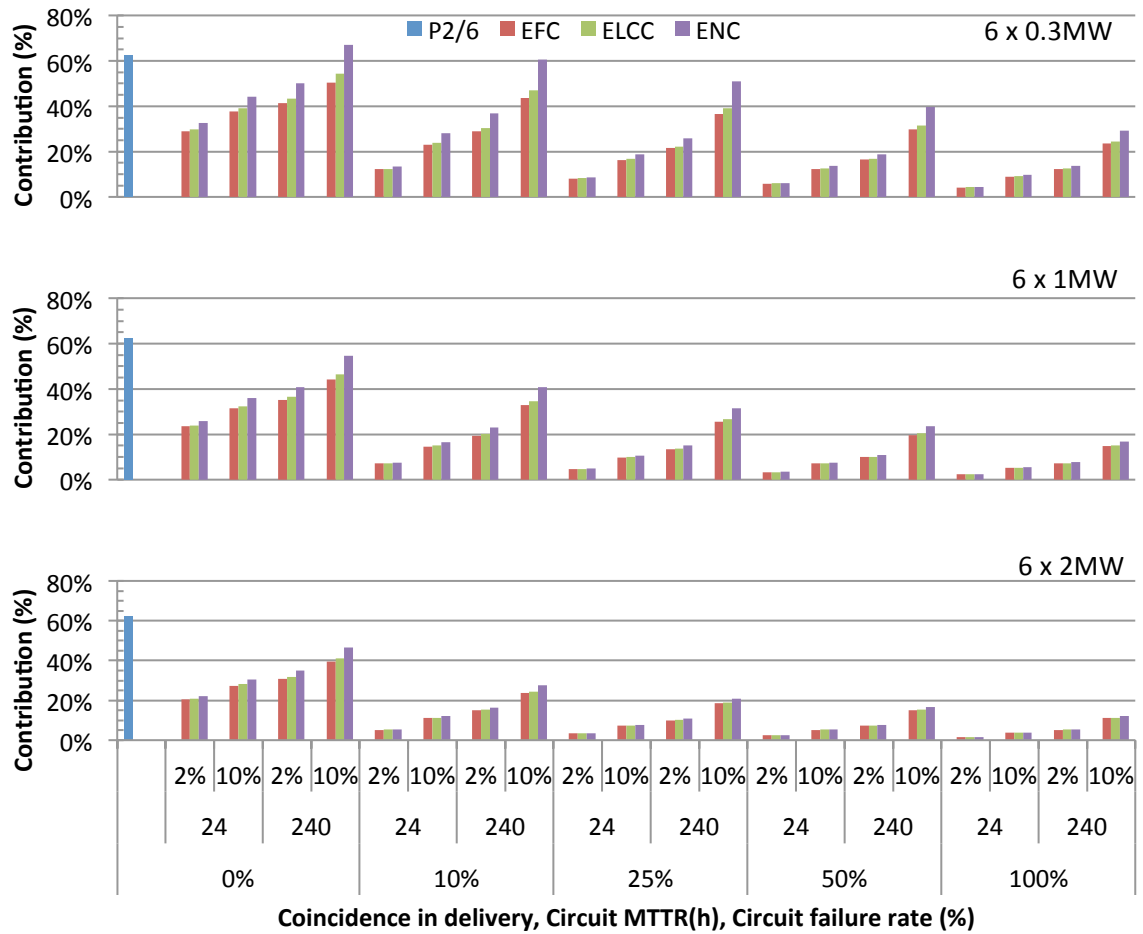


Figure 62: Capacity credit of six demand-led DSR facilities for different capacities 6 x 0.3 MW (top), 6 x 1 MW (middle) and 6 x 2 MW (bottom)

It can be seen that the capacity contribution decreases as coincidence in delivery increases and also as the ratios of demand reduction capacity and circuits' capacity increase. The EFC, ELCC and ENC approaches typically result in a lower contribution than the P2/6 approach. It should be noted that P2/6 contribution is independent of DSR penetration level, network capacity and reliability.

The impact on EENS for the EFC and P2/6 approaches are shown in Figure 63 and Figure 64, respectively.

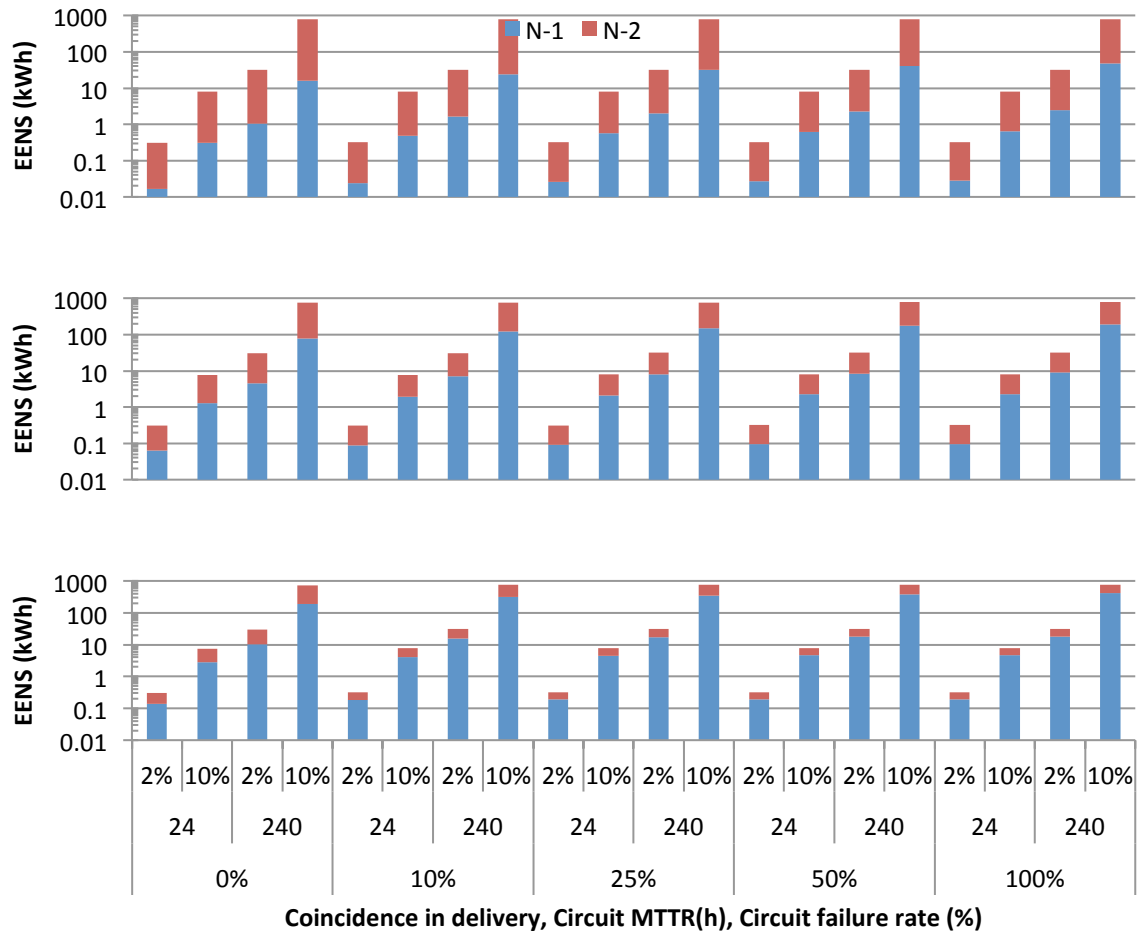


Figure 63: EENS in EFC approach for six demand-led DSR facilities for different capacities 6 x 0.3 MW (top), 6 x 1 MW (middle) and 6 x 2 MW (bottom)

Using the EFC approach, the EENS remains similar irrespective of coincidence in delivery. It slightly increases as the ratio of demand reduction capacity and circuit capacity increase by increasing the contribution to EENS from the N-1 condition.



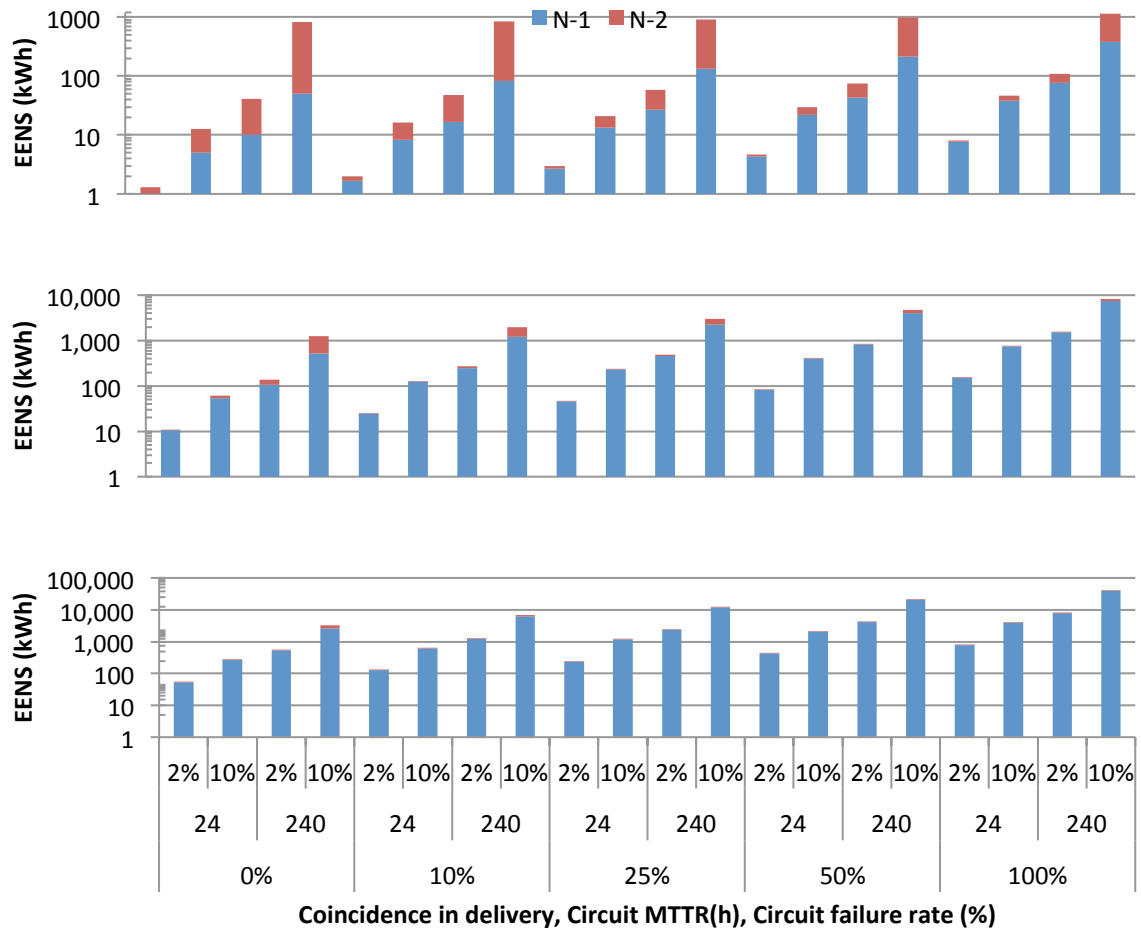


Figure 64: EENS in the P2/6 approach for six demand-led DSR facilities for different capacities 6 x 0.3 MW (top), 6 x 1 MW (middle) and 6 x 2 MW (bottom)

However, using the P2/6 approach the EENS increases as coincidence in delivery increases. The increase is due to the increase in EENS caused by the N-1 condition, while the EENS caused by the N-2 condition remains the same. The EENS significantly increases as the ratio of demand reduction capacity and circuit capacity increase due to the increasing contribution to EENS caused by the N-1 condition. For high ratios of demand-led DSR capacity and circuit capacity and high coincidence in delivery the majority of EENS is due to the N-1 condition.

## 5.6 Value of Unserved Energy

To illustrate the impact on the cost of expected unserved energy, an example involving 50% coincidence in delivery, a circuit reliability parameters failure rate of 10% and MTTR of 24h is used. Two cases are considered: DSR capacities of 0.3 and 2 MW, corresponding to total demand reduction capacities for six facilities of 1.8 and 12 MW. The Value of Lost Load is assumed at £16/kWh. The high range in cost of expected unserved energy can be seen in Figure 65. The two graphs are identical except that the Y-axis and for the right-hand graph has a logarithmic scale.

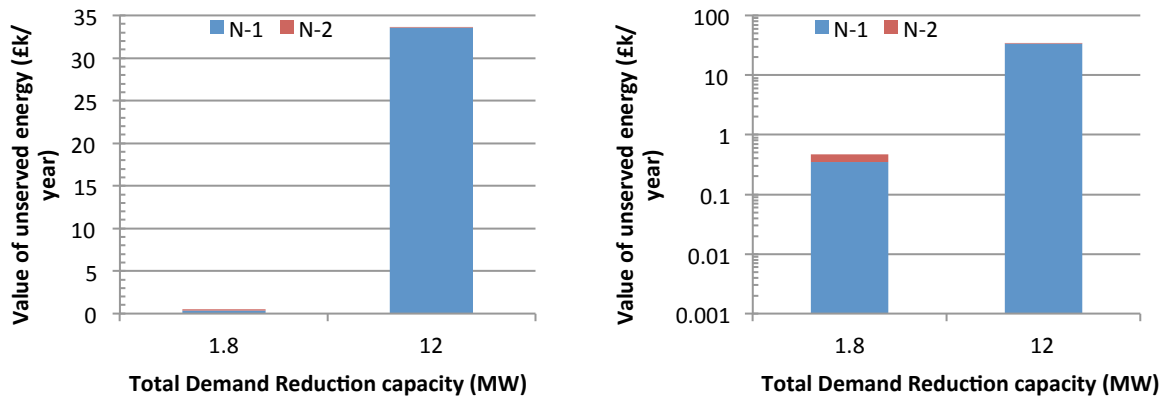


Figure 65: Comparison of value of expected unserved energy for six demand-led DSR facilities if the capacity of each facility is 0.3 or 2 MW

The cost of expected unserved energy is significant for high penetration of demand-led DSR, in which case traditional network reinforcement might be more economic solution. In this context, fundamental review of ER P2/6 will include consideration of costs of traditional and smart grid solutions (e.g. DSR) in enhancing network capacity and the corresponding benefits delivered to end consumers, so that a business case for alternative solutions to enhancing network capacity can be established.

### 5.7 Key Observations and recommendations

Based on a range of successful demonstration and trials carried out in Low Carbon London project, UK Power Networks has developed a number of generation-led and demand-led DSR schemes to substitute for network reinforcement. The capacity contribution of these DSR schemes is quantified following the philosophy of the present P2/6 used to calculate capacity contribution of DG. The P2/6 approach applies reliability modelling of individual non-network technologies without considering the actual distribution network. However, the reliability delivered to end consumers is ultimately driven by the reliability characteristic of both the actual network and DSR.

To analyse impact of the network reliability on the contribution of DSR, this work compares the levels of capacity contribution that correspond to the different definitions established for the network adequacy studies: ELCC, EFC and ENC.

The ELCC, EFC and ENC approaches consider network reliability in quantifying the contribution to security of supply of DSR. Therefore, the level of DSR contribution, measured by the ELCC, EFC and ENC approaches, depends on the reliability of the network (this is not considered in P2/6 approach). The level of DSR contribution, measured by ELCC, EFC and ENC approaches have relatively similar performance, especially for ELCC and EFC approaches.

In highly reliable networks the ELCC, EFC and ENC methods allocate much lower contribution to DSR and hence would result in lower increase of Group Demand when compared with P2/6. ENC method and P2/6 produce similar contributions in networks with low reliability (for example, failure rate of 20% and MTTR of 240 hours). Furthermore, the ELCC, EFC and ENC contributions reduce with (i) increase in penetration level of DSR and (ii) with coincidence in delivery (common mode failure).

EENS is relatively stable for ELCC, EFC and ENC approaches when compared with the P2/6 approach and the EENS for the P2/6 approach depends significantly on (a) the volume of DSR when compared with the

size of Group Demand and (b) the existence of common mode failure - effects that are ignored in the P2/6 approach. In this context, the reliability of the network with DSR, when capacity credit is determined by the P2/6 approach, is significantly lower than compared with other methods for deriving DSR capacity value, particularly in highly reliable networks. For example, in the case of the circuit failure rate being 2%, MTTR being 24 hours and with three DSR facilities, the EENS is more than 15 times larger than ENC method. In networks with lower circuit reliability these differences are much smaller.

If DSR facilities cannot run in islanding operation then ELCC, EFC and ENC contributions are zero when network is supplied by two circuits. It is assumed that demand under demand-led DSR can deliver its contribution even in islanding mode, as contracted demand can be interpreted as demand reduction.

Given the key objective of this work, focused on assessing the reliability performance of distribution network when DSR is used to defer network upgrades driven by load growth, the following recommendations are drawn:

- When applying the ER P2/6 approach to quantifying the contribution of DSR to security of supply, it would be important to assess the implication on reliability supply, particularly in the context of the Interruption Incentive Scheme; in this context, the alternative methods for quantifying capacity contribution of DSR implemented in this work (ELCC, EFC and ENC) would provide useful insights;
- Consideration of diversity and common mode failures of DSR may be relevant when using DSR to substitute for network reinforcement;
- Contractual redundancy improves the probability of delivering the P2/6 contribution and it may be considered in the context of enhancing reliability of supply delivered to end customers and increasing robustness against common mode failures;
- When evaluating the contribution to security of supply of DSR, relative volume of DSR in the context of the size of Group Demand should be considered.

Although this analysis identified a number of weaknesses of the present standard, ER P2/6 based-evaluation of the contribution of DSR, as carried out in [19] (which is then used to establish contracts with DSR following Low Carbon London Trials), is fully justified as ER P2/6 is the existing network standard and only available framework for quantifying capacity contribution of DSR. However, ER P2/6 will be fundamentally reviewed shortly and in the context of the work presented in this report, it will include consideration of costs of traditional and smart grid solutions (e.g. DSR) in enhancing network capacity and the corresponding benefits delivered to end consumers, so that a business case for alternative solutions to enhancing network capacity can be established.

## 6 Key Learning Points

The main learning points resulting from the network-centric reliability modelling are summarised below.

- The P2/6 approach ascribes the same contribution to security of supply to distributed generation irrespective of the network setting;
- The contribution to security of supply varies significantly with respect to the supplying circuit reliability (EFC, ELCC and ENC approaches);
- DSR facilities cannot contribute to security of supply if they cannot run in islanding mode and if the Group Demand is supplied from two-transformer substation;
- Expected energy not supplied does not change significantly due to high circuits availability i.e. probabilities of N-1 and N-2 circuit conditions are small;
- Probability of demand-led DSR delivering contribution estimated by the P2/6 approach increases significantly with N-1 and N-2 facilities redundancy i.e. probability of supplying Group Demand is high given high availability of circuits;
- EFC and ELCC approaches are more robust than ENC approach;
- DSRs number, penetration level and coincidence in delivery significantly influence the contribution to security of supply;
- P2/6 contribution to security of supply can result in high impact event when network circuit performance is low but impact can be reduced by reducing repair time.

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## Project Overview

Low Carbon London, UK Power Networks' pioneering learning programme funded by Ofgem's Low Carbon Networks Fund, has used London as a test bed to develop a smarter electricity network that can manage the demands of a low carbon economy and deliver reliable, sustainable electricity to businesses, residents and communities.

The trials undertaken as part of LCL comprise a set of separate but inter-related activities, approaches and experiments. They have explored how best to deliver and manage a sustainable, cost-effective electricity network as we move towards a low carbon future. The project established a learning laboratory, based at Imperial College London, to analyse the data from the trials which has informed a comprehensive portfolio of learning reports that integrate LCL's findings.

The structure of these learning reports is shown below:

|                                                 |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |
|-------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Summary                                         | SR DNO Guide to Future Smart Management of Distribution Networks                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |
| Distributed Generation and Demand Side Response | <ul style="list-style-type: none"><li>A1 Residential Demand Side Response for outage management and as an alternative to network reinforcement</li><li>A2 Residential consumer attitudes to time varying pricing</li><li>A3 Residential consumer responsiveness to time varying pricing</li><li>A4 Industrial and Commercial Demand Side Response for outage management and as an alternative to network reinforcement</li><li>A5 Conflicts and synergies of Demand Side Response</li><li>A6 Network impacts of supply-following Demand Side Response report</li><li>A7 Distributed Generation and Demand Side Response services for smart Distribution Networks</li><li>A8 Distributed Generation addressing security of supply and network reinforcement requirements</li><li>A9 Facilitating Distributed Generation connections</li><li>A10 Smart appliances for residential demand response</li></ul> |
| Electrification of Heat and Transport           | <ul style="list-style-type: none"><li>B1 Impact and opportunities for wide-scale Electric Vehicle deployment</li><li>B2 Impact of Electric Vehicles and Heat Pump loads on network demand profiles</li><li>B3 Impact of Low Voltage – connected low carbon technologies on Power Quality</li><li>B4 Impact of Low Voltage – connected low carbon technologies on network utilisation</li><li>B5 Opportunities for smart optimisation of new heat and transport loads</li></ul>                                                                                                                                                                                                                                                                                                                                                                                                                            |
| Network Planning and Operation                  | <ul style="list-style-type: none"><li>C1 Use of smart meter information for network planning and operation</li><li>C2 Impact of energy efficient appliances on network utilisation</li><li>C3 Network impacts of energy efficiency at scale</li><li>C4 Network state estimation and optimal sensor placement</li><li>C5 Accessibility and validity of smart meter data</li></ul>                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |
| Future Distribution System Operator             | <ul style="list-style-type: none"><li>D1 Development of new network design and operation practices</li><li>D2 DNO Tools and Systems Learning</li><li>D3 Design and real-time control of smart distribution networks</li><li>D4 Resilience performance of smart distribution networks</li><li>D5 Novel commercial arrangements for smart distribution networks</li><li>D6 Carbon impact of smart distribution networks</li></ul>                                                                                                                                                                                                                                                                                                                                                                                                                                                                           |





Low Carbon London Learning Lab



MAYOR OF LONDON



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