

Contribution of energy storage and demand-side response to security of distribution networks

Ioannis Konstantelos¹ ✉, Predrag Djapic¹, Goran Strbac¹,
Panagiotis Papadopoulos², Adriana Laguna²

¹Department of Electrical and Electronic Engineering, Imperial College London, London, UK

²UKPN, London, UK

✉ E-mail: i.konstantelos@ic.ac.uk

Abstract: The smart grid paradigm envisages the wide penetration of distributed energy resources, such as demand-side response (DSR) schemes and energy storage (ES). Despite their potential to improve security of supply at the distribution level, existing design standards in most jurisdictions consider solely conventional assets; conceptual and methodological gaps prevent DSR and ES from being embedded into formal network design practices. As such, the crucial question that arises is how to assess the security contribution of these technologies so as to level the playing field and encourage the transition to a smart grid. Here, the authors introduce two capacity metrics: equivalent firm capacity and equivalent load-carrying capability. The authors describe their application to DSR and ES, showcase results from the UK Power Networks' Smarter Network Storage and Low Carbon London projects, and provide suggestions on the incorporation of smart assets in future design standards.

1 Introduction

Distribution network security has traditionally relied on conventional assets such as transformers and circuits to supply energy to consumers from the upstream grid. In recent years, there has been increasing interest for utilising non-networks assets to improve cost efficiency and increase security of supply. For example, in the UK, the present distribution network planning standard, Engineering Recommendation P2/6, was updated in 2006 to include distributed generation (DG) resources when assessing a network's security level [1]. Nevertheless, other non-network approaches such as demand-side response (DSR) and energy storage (ES) are still not considered in the current planning standard. Considering that the current projections by National Grid [2] state that the volume of distribution-connected ES could be up to 13.2 GW by the year 2040 as well as the growing interest in DSR, it is imperative that the potential contribution of these resources is acknowledged and used to improve the security and cost-efficiency of distribution networks. Similar regulatory gaps exist in many jurisdictions around the world, undermining the transition to a cost-effective future electricity system [3].

The first step in formally remunerating a DSR scheme's or ES plant's ability to contribute to security of supply is to compute its capacity credit. Until now, researchers have primarily focused on capacity credit methodologies for DG resources. Comprehensive overviews of different methods for calculating the contribution of conventional and renewable generation are provided in [4–6]. In contrast, there have been very limited efforts to extend the concept of capacity credit to DSR and ES; a number of conceptual and methodological obstacles remain unaddressed.

In the remaining of the paper, we first introduce and discuss the characteristics of DSR and ES that differentiate them from conventional assets and DG. We proceed by proposing methodologies for computing two capacity credit metrics: equivalent firm capacity (EFC) and equivalent load-carrying capability (ELCC) [7]. Through the use of case studies, we explore the suitability of these metrics and discuss the impact of different drivers to security contribution.

2 Characteristics of ES and DSR

ES and DSR abide to different operation principles when compared with conventional assets. First of all, whereas conventional resources, such as DG, typically face only power constraints, storage facilities can face both power and energy constraints. The ability of ES to support supply does not depend solely on the asset's technical characteristics but also on its preceding state-of-charge (SOC). A second point is that whereas fuel supply of DG is considered infinite or stochastic, ES's SOC is tightly linked to the network's available transfer capability. This is because ES does not generate power but rather makes use of existing network assets to draw power from the upstream grid. As such, whereas transformer outages do not have an impact on DG's output capability (if islanded operation is feasible), in the case of ES, they reduce its ability to store energy by limiting charging capability. A third aspect, which is a direct implication of the presence of energy constraints, is that the shape of demand plays a major role when determining security contribution; two demand profiles that have the same peak level but different shapes during the day lead to different charging capability and discharging requirements. For example, a flat demand profile presents far fewer opportunities for charging compared with a peak demand profile, thus leading to a reduced contribution.

DSR schemes can exhibit a combination of characteristics of DG and ES. If load recovery is limited, meaning that the demand-side action involves consumption reduction and no subsequent increase, then the DSR can be treated as DG. In this case, the security contribution is driven solely by power constraints. However, if the load recovery is prominent, as would be the case for thermostatic loads, then DSR can be viewed as an ES; security contribution is driven by both power and energy constraints.

The issues discussed above are fundamental to the security contribution of ES and DSR; a capacity credit methodology that considers them must accommodate two important aspects. First of all, chronological simulation is essential to capture energy constraints, temporal demand characteristics, and model the dependence to preceding states of charge. Second, modelling of

network faults is necessary since the ability to recharge is tied to the available network capacity. As explained in the following sections, the current practice does not meet these two requirements. In this paper, we provide an extension for accommodating chronology in the current UK design standard. Subsequently, an alternative methodology based on ELCC is introduced that meets the above criteria. The data presented in this paper were obtained from two projects: Smarter Network Storage (SNS) and Low Carbon London (LCL) by UK Power Networks.

3 Extending the current approach

According to the current P2/6 design standard, a capacity credit for the DG is defined based on the concept of EFC. EFC represents the circuit capacity which is equivalent to the DG and is the value by which group demand can increase due to the presence of DG. EFC can be calculated as the amount of capacity of an ‘always available’ network connection which can replace DG while maintaining the same supply risk level. The principal risk metric used for this type of assessment is the expected energy not supplied (EENS).

According to P2/6, the capacity credit of DG is based on the scaled load duration curve (LDC) of the demand to be served and the asset’s power rating. As shown in Fig. 1, EENS is computed as the weighted sum of the EENS that arises when DG is offline [(as shown in Fig. 1a) this is the entire annual energy to be served] and online (Fig. 1b); the weights are determined according to a location and technology-specific availability factor α (e.g. 30% for wind in a specific area). The EFC is defined as the y-axis intercept corresponding to the computed EENS (Fig. 1c).

In a similar vein, the concept of EFC can be extended to an ES plant (or a DSR scheme with load recovery). As illustrated in Fig. 2, a network supplying group demand D and equipped with a storage plant is equivalent to a network with an ‘always available’ circuit of Y MW, where Y is the plant’s EFC.

Nevertheless, a number of modifications and assumptions need to be made to accommodate ES in this capacity credit methodology. The current philosophy calculates the contribution of an asset without considering the distribution network. This approach is sensible in the case of conventional assets and DG, where the main driver of capacity credit is their power rating and availability. However, ES operation is tied to the upstream network. As such, the P2/6 ‘isolation’ approach can capture only one of the multiple sources of security contribution; peak shaving. As shown in Fig. 3, we assume that the ES plant is tasked with providing security of supply during the peak hours of each day, e.g. between

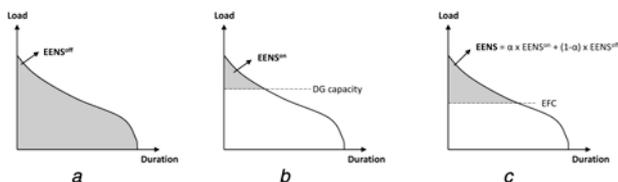


Fig. 1 Graphical representation of EFC calculation for DG under the current standard P2/6

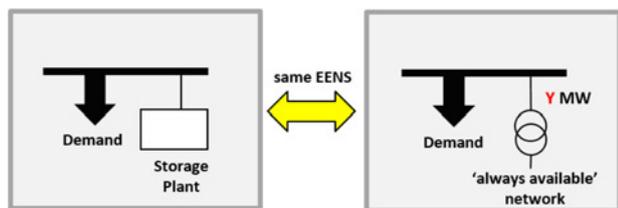


Fig. 2 Equivalence between ES and firm capacity

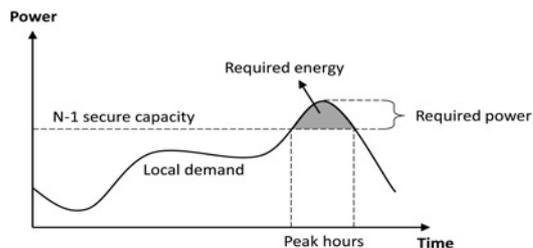


Fig. 3 Peak shaving function

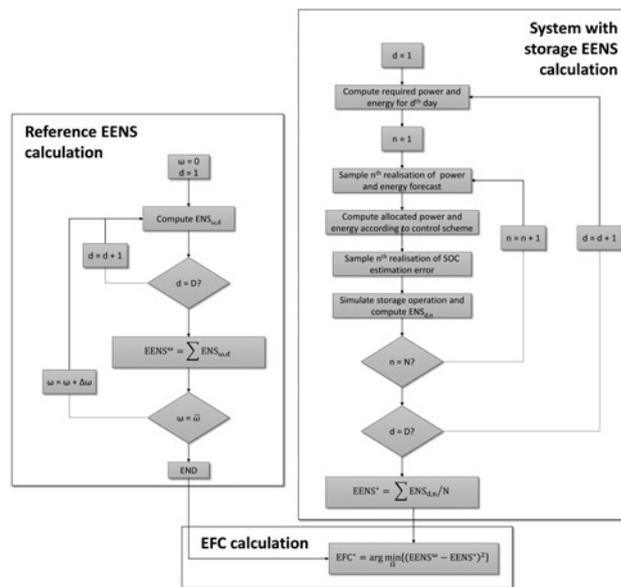


Fig. 4 Algorithm flowchart for calculating EFC of ES

2 and 8 p.m., to cover the residual load exceeding the network’s secure capacity limit while recharging occurs at night. Note that the ES operator may not have perfect information regarding the power and energy shortfall of the next day and the operator must allocate power and energy day-ahead while running the risk of under- or over-allocation; this aspects captures the fact that ES may not be fully dedicated to peak shaving but may be carrying other competing functions such as energy arbitrage. A final consideration that pertains to fuel cells is that operation may suffer from SOC estimation errors.

Modelling based on LDCs does not apply to ES; chronological simulations within a Monte Carlo framework that adequately samples all sources of variability (e.g. residual demand shape, forecast error etc.) are necessary. The model’s input parameters include the load time series, the storage plant’s power and energy capability, power and energy forecasting errors, as well as SOC estimation errors. As can be seen in Fig. 4, the framework consists of three steps (i) computing the EENS* of the ES-equipped system through a large number of simulations, (ii) calculate a set of reference EENS values for different circuit sizes, and (iii) find the circuit rating equivalent to the downstream capacity made available by the ES.

3.1 Leighton Buzzard case study

Data from the Leighton Buzzard primary substation for the first half of 2015 are used in this section to compute the security contribution of the SNS plant; the largest ES plant in Great Britain. The ES plant is rated at 6 MW with a 10 MWh capacity. According to the data, there is limited need for peak shaving; the most binding day entails a power and energy shortfall of 2.8 MVA and 5.8 MWh,

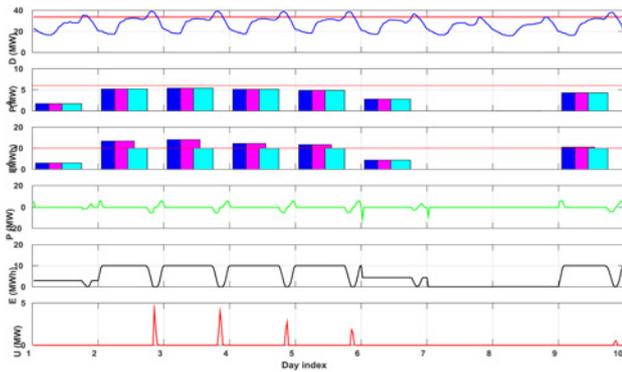


Fig. 5 Simulation of the Leighton Buzzard plant

respectively. By connecting the ES, we reduce EENS from 96.6 to 0 MWh; peak shaving is carried out successfully at all times and the plant has an EFC equal to 2.8 MW, i.e. 100% of the maximum shortfall.

To comprehensively demonstrate the proposed EFC methodology, we analyse more cases of power shortfalls by artificially lowering the network's transfer limit. For example, in Fig. 5, we show some days of the simulation of the ES plant under a maximum power shortfall of 6 MW. The top panel shows the group demand in blue and the substation transfer limit in red; the second and third panel show the daily power and energy predicted, actually required and eventually allocated in blue, purple, and cyan bars, respectively (perfect predictions assumed here); the red horizontal lines denote the power and energy ES limits. The remaining panels show ES charge/discharge, SOC, and curtailed demand. According to the simulation, EENS was computed to be 10.70 MWh due to energy constraints. As can be seen in Fig. 6, the corresponding EFC is 4.07 MW, i.e. 67.8%.

Normalised EFC values for ES of different sizes under power shortfalls of 2, 4, 6, and 8 MW are shown in Fig. 7 (note that energy capacity is shown in terms of hours with respect to the ES power rating). In cases of a low power shortfall, the peak shaving

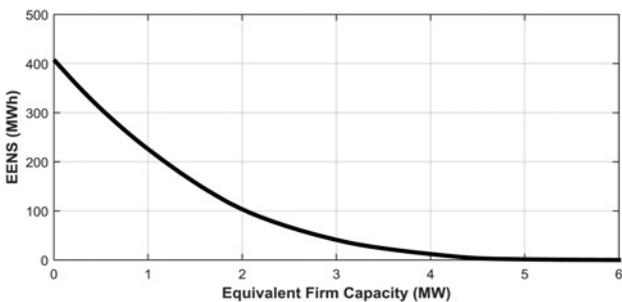


Fig. 6 EENS versus EFC curve

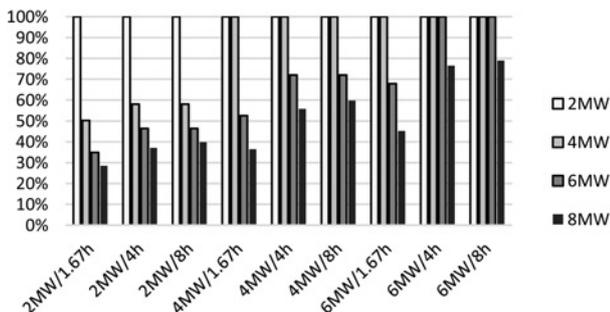


Fig. 7 EFC for different ES sizes and power shortfalls

Table 1 EFC of Leighton Buzzard ES (6 MW/10 MWh); case studies on efficiency were carried out with $\varphi = 0.60$

$\alpha, \%$	EFC, %	$\varphi, \%$	EFC, %	$\epsilon, \%$	EFC, %
100	67.8	0	67.8	100	27.2
99	64.7	0.25	53.8	90	27.0
95	54.3	0.50	30.7	80	26.7
90	46.7	0.75	21.3	70	26.3

requirements can be fully met even for smaller-sized ES. As the power shortfall increases, energy requirements start increasing considerably. Power constraints arise in all cases where the shortfall is greater than the ES power rating.

In Table 1, we show the impact of plant availability (α), charging efficiency (ϵ), and demand flatness (φ). For the latter case studies, we modify basecase demand time series $d'_t = d_t + \varphi(E_t\{d_t\} - d_t)$; at $\varphi = 1$, we have a fully flat demand profile at the average value $E_t\{d_t\}$.

In the analysis on plant availability α , we assume that ES resumes operation at its original SOC; this is usually the case for fuel cell batteries. As can be seen in the table, α is a very substantial driver of EFC. This effect is more pronounced for ES plants that have high contribution at $\alpha = 100\%$ and less pronounced for plants that already face energy/power constraints in the basecase; this is due to the non-linear relationship between EENS and EFC (Fig. 6). Demand flatness is also a very important determinant of security contribution; the flatter the demand, the higher the energy requirements and thus the lower the EFC. In addition, a flat demand profile generally entails inferior charging capability. Note that this effect can be alleviated with DG connections. For example, we found that in the case of flat demand profiles, solar plants can increase ES contribution by enabling further charging during midday. As shown in Table 1, charging efficiency has a marginal impact overall. For example, in the basecase of $\varphi = 0$, efficiency has no impact on EFC. The effect becomes apparent only for much flatter demand profiles, when energy constraints arise due to a reduced charging overhead; efficiency losses thus lead to binding situations. Additional case studies were carried out regarding the impact of forecasting errors with respect to the power/energy daily requirements. Overall, forecast errors have only a minor impact on EFC values and over-allocation strategies were shown to mitigate adverse realisations. Finally, SOC estimation errors are generally low and do not interfere with operation; the error levels observed at Leighton Buzzard were below 1% and were found to have no impact on EFC.

4 Introducing ELCC for ES and DSR

Currently, one of the main tenets of the P2/6 philosophy is ignoring the reliability of the existing distribution network. In this paper, we propose a new framework based on ELCC. ELCC is defined as the amount of constant load that can be added to a system equipped with ES resulting in the same EENS as the original network without ES (referred to as the 'basecase') [8]. ELCC is expressed in terms of MW, while normalised ELCC refers to the ratio of ELCC over the ES power rating. In this framework, ES is not used for peak shaving as before, but employed to sustain supply during network faults. Note that the application of ELCC to ES is currently being discussed in some jurisdictions (e.g. [9]).

4.1 ELCC of ES

An event-driven chronological Monte Carlo framework has been developed to simulate ES operation across a very large number of network faults whose frequency and duration are randomly sampled from exponential probability distributions. A root-finding algorithm has been deployed to compute ELCC; note that each iteration entails the simulation of a very large number of years of ES operation (in the order of 10^6). This method has been applied

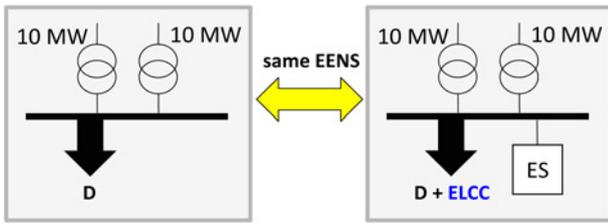


Fig. 8 Basecase (left) and system with ES (right)

to the network shown in Fig. 8 consisting of two 10 MW transformers subject to failure. In this section, we compute the ELCC of ES plants of various sizes under different scenarios of transformer mean time between failure (MTBF) and mean time to repair (MTTR). The level of peak demand D depends on the assumed redundancy level; we have applied $N - 1$, i.e. $D = 10$ MW.

An example simulation of annual operation of a 2 MW/10 h ES plant at a network with peak demand of 13 MW is shown in Fig. 9. As can be seen, demand curtailment is driven by single and double outage events.

In Fig. 10, we show ELCC values (normalised in terms of each plant's power rating) for ES plants of different sizes under four MTTR scenarios. As expected, larger energy capacity leads to higher contribution, less reliable networks (i.e. large MTTR) lead to lower ES contribution since network outages last longer. This is primarily because during double outages, the ES will need to have enough energy stored so as to fully sustain the extra demand while not being able to periodically recharge. This clearly demonstrates the intricate relationship between ES contribution and network reliability. Another interesting output of our analysis is that ELCC is not very sensitive to MTBF; for example, no difference was identified between networks with transformer MTBF of 1 and 5 years. Although this is counter-intuitive, the reason is that realistically sized storage plants at the distribution level (i.e. a few megawatt hour) can charge to their maximum energy capacity well before the next outage event occurs in both cases. MTBF has a

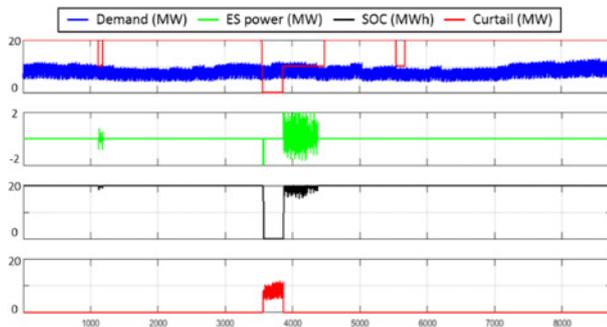


Fig. 9 Example simulation of annual ES operation

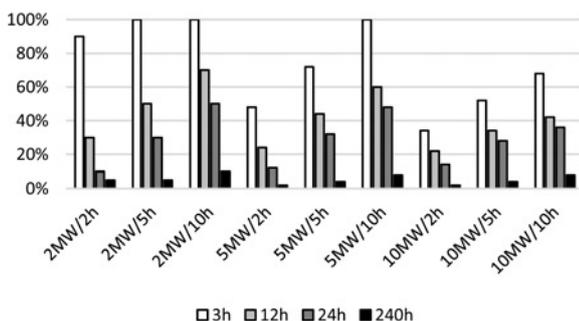


Fig. 10 ELCC of ES plants under MTTR scenarios

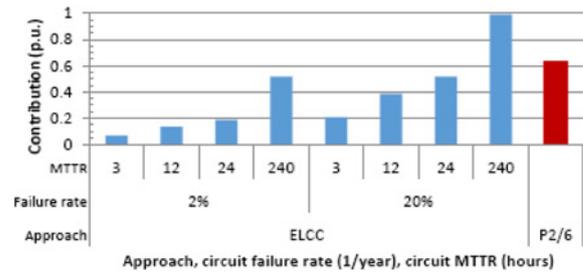


Fig. 11 ELCC of DSR under MTTR scenarios

substantial impact when it is too low, leading to frequent outages, or when dealing with large ES plants that charge over very long periods.

4.2 ELCC of DSR

In this section, we investigate the ELCC of DSR with no load recovery, i.e. reducing demand in the event of a fault. In Fig. 11, we show the contribution for a 2 MW DSR scheme and an availability of 90% applied to a system with two 20 MW circuits and $N - 1$ redundancy; x -axis refers to different circuit MTTR (hours), while 2 and 20% refer to the circuit failure rate (1/year). As can be seen, the ELCC contribution increases from $\sim 7\%$ for the reliable network up to 100% for the unreliable case; unreliable networks stand to gain substantially from a DSR scheme because it is easier to improve upon a basecase with increased demand curtailment. Recall that the opposite pattern was observed for ES, since ES operation is tightly linked to having reliable access to the network. In addition, we contrast the obtained ELCC contributions to the contribution obtained under the existing P2/6 standard (63%) which does not depend on specific network reliability metrics. As can be seen, the existing approach can lead to severe over/under-estimations. Additional studies also indicated that when having multiple DSR schemes, coincidence of availability is important.

5 Conclusions

In this paper, we have investigated the security contribution of ES and DSR under two frameworks: (i) peak shaving capability using the current approach P/6 based on EFC and (ii) capability to sustain supply during faults using the ELCC metric. Data were acquired from the SNS and LCL projects with UK Power Networks. By developing a suitable methodology based on chronological Monte Carlo simulation, we have demonstrated how the existing standard can be expanded to accommodate ES. Further studies were carried out to demonstrate the materiality of additional drivers such as plant availability, efficiency, and demand shape. Regarding ELCC, one of the key results obtained is that the security contribution of DSR and ES varies considerably depending on network reliability. The absence of such considerations within the existing EFC-based UK framework, which depends solely on a plant's technical characteristics, was highlighted. As such, the results of our analysis underline the need to rethink some fundamental aspects of the existing standards and bring forward novel suggestions for the accommodation of demand-side and storage resources. Nevertheless, the best approach to incorporating the above insights into a standard remains an open question. As mentioned in [6], mandating a methodology that entails complex modelling could increase the administrative burden and negatively affect the uptake of distributed ES. As such, in the future, we aim to further investigate the codification of ES and DSR security contribution.

6 References

- 1 Electricity Networks Association: 'Engineering Recommendation P2/6: Security of Supply', 2006
- 2 National Grid: 'Energy Future Scenarios', 2016
- 3 Strbac, G., Konstantelos, I., Pollitt, M., *et al.*: 'Delivering future-proof energy infrastructure', 2016
- 4 Task Force on the Capacity Value of Wind Power: 'Capacity value of wind power', *IEEE Trans. Power Syst.*, 2011, **26**, pp. 564–572
- 5 Milligan, M., Porter, K.: 'Determining the capacity value of wind: an updated survey of methods and implementation'. Proc. Wind-Power, Houston, TX, 2008
- 6 Amelin, M.: 'Comparison of capacity credit calculation methods for conventional power plants and wind power', *IEEE Trans. Power Syst.*, 2009, **24**, (2), p. 6850691
- 7 Garver, L.: 'Effective load carrying capability of generating units', *IEEE Trans. Power Appar. Syst.*, 1966, **8**, pp. 910–919
- 8 Billinton, R., Li, W.: 'Reliability assessment of electric power systems using Monte Carlo methods' (Plenum Press, New York, 1994)
- 9 California's Office of Ratepayer Advocates: 'Stakeholder Comments: Regional Resource Adequacy Initiative Issue Paper'. January 2016