A Probabilistic Method combining Electrical Energy Storage and Real-Time Thermal Ratings to defer Network Reinforcement

David M Greenwood, Neal S Wade, Phil C Taylor, Panagiotis Papadopoulos and Nick Heyward

***Abstract*— When a primary substation reaches its capacity limit, the standard solution is to reinforce the network with additional circuits. Under the right conditions, the required additional peak capacity can be provided by energy storage systems (ESS), real-time thermal ratings (RTTR) or a combination of the two. We present a probabilistic method for calculating the size of an electrical energy storage system for a demand peak shaving application. The impact of both power and energy capacity are considered, along with the reliability of the energy storage and the existing overhead lines. We also consider the combination of energy storage and RTTR – taking advantage of the inherent variability in power line rating as a result of changing weather conditions – for enhancing reliability, deferring conventional reinforcement and increasing the availability of energy storage to participate in commercial service markets. The method is demonstrated in a case study on a network with an ongoing 6 MW/10 MWh ESS innovation project.**

***Index Terms*—Energy Storage, Power Distribution, Power System Planning, Smart Grids**

I. Introduction

ENERGY Storage Systems (ESS) can be installed in distribution networks to perform a variety of network services including voltage control, peak shaving and reactive power compensation [1]. This paper considers issues around an ESS installation primarily motivated by a need for peak shaving. Though the benefits of using an ESS to reduce peak demand have been widely documented, no method has been presented to determine the energy capacity and converter power rating needed to maintain the prevailing security of supply standards at any given site. This is a necessary step in evaluating the viability of an ESS project.

The first contribution of this paper is providing such a method, using probabilistic analysis of the demand and a model for the operational constraints of the ESS. The reliability of both the existing network components and the ESS are accounted for, and the impact of different levels of ESS reliability is assessed. Reinforcement via an ESS has several potential advantages compared with conventional reinforcement; it can help solve other network problems, for example over voltage on the local network; it does not require the same long planning process, nor does it result in the same long-term lock-in; it can gain revenue through participating in ancillary service markets. The method also quantifies the utilization of the ESS for peak shaving, allowing assessment of how often it could be made available for these other services. A case study is presented, based on UK Power Networks' Smarter Network Storage project [2].

The second contribution extends the method to examine deployment of ESS alongside Real-Time Thermal Ratings (RTTR). RTTR is an emerging technology which allows network operators to take advantage of the inherent variation in network capacity as environmental conditions fluctuate [3]. This leads to an increased rating, with respect to conventional approaches, the majority of the time, particularly in the case of an overhead line (OHL) [4]. There are also circumstances in which the rating of a conductor falls below its static rating; using RTTR makes network operators aware of this and allows them to take action to avoid overloading circuits and jeopardizing system security. While the benefits of RTTR are qualitatively well known [5], our extended method quantifies how effective the combination of ESS and RTTR can be at deferring or preventing network reinforcement, compared with using each technique in isolation.

A. Peak Shaving

Peak Shaving (PS) refers to the reduction of electricity demand at times of peak consumption. Electricity demand varies throughout the day; in the UK the peak typically occurs in the early evening, and is greatest during winter. In the majority of cases, the peak only occurs for a small fraction of the time [6], but the generation, transmission and distribution systems must be designed to accommodate it. A peak shaving scheme attempts to reduce the peak by offsetting demand via distributed generation, demand side response or ESS [7].

For illustration of this concept, Fig. 1 shows the demand over 24 hours at a primary substation (33/11kV) in the UK. Between 17:00 and 20:00, the demand exceeds the OHL limit, so the ESS would need to provide peak shaving for those 3 hours. The peak exceeds the demand by around 4 MVA, so the ESS would need a converter rated at 4 MVA. Finally, the total area between the demand curve and the line rating is around 8 MWh; this is the energy capacity that would be required for the ESS to meet the peak shaving demand.

B. Sizing ESS for Peak Shaving

In this section, research on the use of ESS to reduce peak demand in distribution networks is critically reviewed. The limitations of the existing methods used to determine how large an ESS is required, in terms of power and energy to ensure security of supply, are highlighted.

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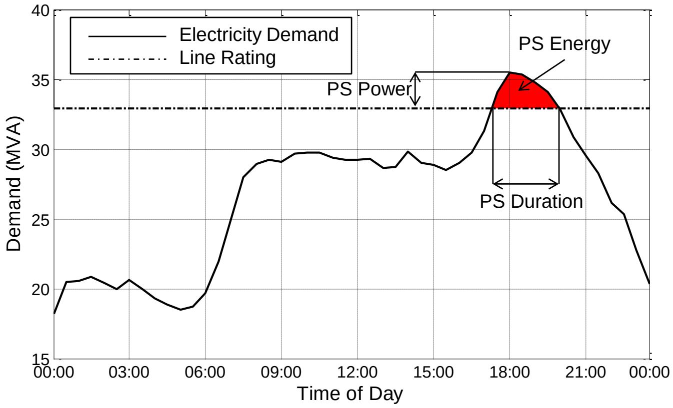

Fig. 1. Peak shaving needs to take place when the existing infrastructure cannot support the demand peak. A storage system would need to meet both power and energy requirements to successfully offset the peak.

Battery sizing for peak shaving was considered by *Oudalov et al.* [8]. The authors consider peak reduction to reduce energy supply costs, rather than a security of supply application. The context presented is that industrial customers pay a significant proportion of their bill based on the 15 minute period with the greatest demand over the year. The method used is a simple cost-based optimization; while this is sufficient for the chosen application, the method cannot be applied for security of supply, because the consequences of inadequately sized storage would be more severe than in a purely economic deployment.

Nick et al. [9] investigate the size and location of ESS in an active distribution network. They remove the limitation that a real ESS project could be physically large, and allow it to be sited at any node in the network; consequently, the problem becomes more complex than it would be in a real network, where limitations on available land would reduce the number of appropriate locations considerably. In the example given, the authors set the total power and energy ratings of all storage in the network, and optimization is used to allocate proportions of this capacity to various nodes. A similar approach is used in [10], though in this case the system is broken down into micro-grids, each containing combinations of DG and ESS in various configurations. The total capacity of ESS in the system was allowed to increase, and the system's wellbeing was assessed. Although this output would not function as in input to a cost/benefit analysis carried out by a network operator, the results show that system wellbeing increased with the deployment of more ESS. A paper by *Lyons et al.* considers sizing of ESS to accommodate air source heat pumps and photo-voltaic (PV) panels on distribution networks [11]. A variety of power and energy combinations were considered and battery degradation was accounted for. While the authors do consider the amount of heat pumps and PV that could be accommodated by ESS of different sizes, they do not consider accommodation of conventional demand, nor rely on ESS for security of supply.

ESS sizing has been more thoroughly investigated in the context of balancing the power output from wind [12-15] and solar [16] generation. Some of the techniques used may be applicable to a peak shaving application, if peak demand is considered analogous to low generation, and high network capacity resulting from low demand is analogous to high generation.

The economic use of ESS for the provision of multiple services is discussed by [17]. The authors consider large scale storage (for example, pumped hydro) for balancing and load shifting on a large network. Because the storage is considered as the only balancing mechanism, the power rating of the storage is set to the maximum imbalance (15 GW). The capacity of the storage is set to 30 GWh, and is done so arbitrarily.

The existing literature does not address the problem of sizing ESS for peak shaving in distribution networks. Additionally, while the use of ESS alongside distributed generation has been investigated by many authors, the deployment of RTTR and ESS together has not.

C. Real-Time Thermal Ratings and Security of Supply

The power and energy required for PS are a function of the demand and the capacity of the local network. In many cases, the capacity of the network is directly determined by the thermal rating of the OHLs. This thermal rating is considered to be static by network standards but is, in reality, continually fluctuating as a result of changing environmental conditions [3]. Equation (1) shows the energy balance in an OHL; heating is caused by the joule effect (I^2R) and solar heating (q_s), while cooling occurs through convection (q_c) and radiation (q_r).

$$I^2R + q_s = q_c + q_{\mathrm{r}} \tag{1}$$

This variation can be taken advantage of through Real-Time Thermal Rating (RTTR); however, while the true rating of the conductor is greater than the nominal rating the majority of the time, it is, by virtue of the calculation process, below it for a non-trivial amount of time (3%, according to the UK line rating standard [18]). Knowledge of this variable capacity can increase network reliability, particularly in demand growth scenarios [5], but it can also reduce perceived reliability, particularly in the case of networks with lower peak demand [19] – this is because low rating events, which could lead to a potential loss of load, would not be registered with static ratings. These events would still take place if static ratings were in use, but the network operator would be blind to them, potentially resulting in severe consequences.

RTTR schemes have been demonstrated through a variety of research projects, both in the UK and internationally [20-22]. RTTR is relatively inexpensive and quick to deploy, but the rating of the line cannot be controlled, meaning the additional capacity will not always be available when it is required. This weakness can be alleviated by combining RTTR with an ESS, which is a controllable network resource. We investigate whether the presence of the RTTR could reduce the size of required energy storage, and reduce its utilization for peak shaving.

II. Proposed Probabilistic Method

A. Assessing the impact of ESS on supply reliability

The purpose of installing the ESS is to improve reliability for customers without having to build conventional network assets. It is, therefore, essential to be able to quantify how the ESS affects reliability, and see how this result varies for different power and energy ratings. A probabilistic method has been developed to assess this, accounting for the variability in demand, and the reliability of both the existing infrastructure and the ESS. This method allows network planners to quantify the benefits of ESS in terms of Expected Energy Not Supplied (EENS) – a widely used reliability metric, with lower EENS corresponding to higher system reliability.

A Monte Carlo (MC) approach was used – this method depends on a substantial amount of historical data being available, ideally at least 3 full years. In each iteration, the demand profile for an observed day is selected at random from historical data. The state of the network on this day is then determined using the following reliability model:

$$\begin{aligned} k_1 > A_{\mathrm{L1}}, \quad & k_2 > A_{\mathrm{L2}} \rightarrow C = 0, \\ k_1 < A_{\mathrm{L1}}, \quad & k_2 > A_{\mathrm{L2}} \rightarrow C = R, \\ k_1 > A_{\mathrm{L1}}, \quad & k_2 < A_{\mathrm{L2}} \rightarrow C = R, \\ k_1 < A_{\mathrm{L1}}, \quad & k_2 < A_{\mathrm{L2}} \rightarrow C = 2R \end{aligned} \tag{2}$$

where k_1 and k_2 are random numbers between 0 and 1, A_{L1} and A_{L2} are the availability of OHLs 1 and 2 respectively, C is the network capacity and R is the rating of one OHL. The network is assumed to be two OHLs linking the substation to a grid supply point. A diagram of this type of systems is provided in Fig 2. To avoid running unnecessary MC simulations, state space partitioning is carried out, based on the reliability model:

$$\begin{aligned} C = 0, \quad & ENS = E_{\mathrm{Day}} \\ C = R, \quad & ENS = ENS_{\mathrm{MC}} \\ C = 2R, \quad & ENS = 0 \end{aligned} \tag{3}$$

The MC simulation is only carried out if there is a single circuit outage; if the system is intact, ENS is zero, and if there is a double circuit outage, the ENS is equivalent to the entire day's energy consumption, E_{Day}. This reduces the computational burden of the method significantly – a factor of 50 for the case study provided. A similar reliability model is used for the ESS:

$$\begin{aligned} k_3 > A_{\mathrm{ES}} \rightarrow P = 0, \quad & EC = 0 \\ k_3 < A_{\mathrm{ES}} \rightarrow P = P_{\mathrm{Rated}}, \quad & EC = EC_{\mathrm{Rated}} \end{aligned} \tag{4}$$

where k_3 is a random number between 0 and 1, A_{ES} is the availability of the ESS, P is power, and EC is the energy capacity of the ESS. The ESS is modelled as having a finite capacity, and a power rating to constrain the rate of energy exchange. Stored energy at each time step, known as State of Charge, SoC_i, is equal to the stored energy in the previous time step, SoC_{i-1}, minus the power transferred to the grid in that time step, P_i, multiplied by the length of the time step, t_i.

$$P_{Rated} \geq P_i \geq -P_{Rated} \tag{5}$$

$$EC_{Rated} \geq SoC_i \geq 0 \tag{6}$$

$$SoC_i = SoC_{i-1} - P_i . t_i \tag{7}$$

In the examples shown, t is 30 minutes and the energy is considered in MWh, so this becomes:

$$SoC_i = SoC_{i-1} - \frac{P_i}{2} \tag{8}$$

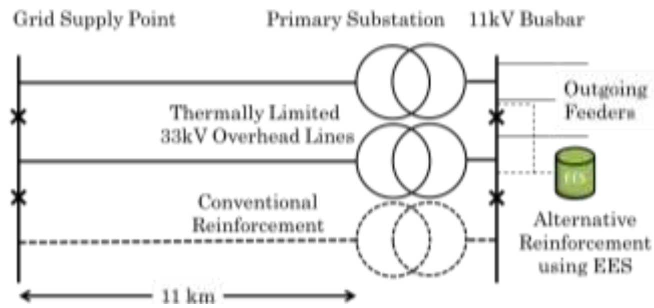

Fig 2. A diagram of the local network showing where the ESS is to be installed. The 33kV OHLs are at capacity with the existing demand, meaning some reinforcement is required – either conventional or an emerging technology.

Fig 3 shows the algorithm used to assess the EENS using an ESS system to support demand. For each day of the simulation, a day of demand data is sampled from the historical demand data, and the reliability state of the ESS and network are calculated. The demand data is sampled with replacement, meaning the same day can be used multiple times in large simulations. At each time step, the difference between the demand and the network capacity is calculated. If the demand is greater than the capacity then the required energy is removed from the ESS. If there is not sufficient power or energy available, then the Energy Not Supplied (ENS) for that day increases. Additional logic covers cases where the power rating is the constraint, or if the power or energy from the ESS can only partially solve the problem.

For each day, the ENS is evaluated; by using results from many days, the Expected Energy Not Supplied is calculated:

$$EENS = \sum_{x=1}^{n} p_x . ENS_x \tag{9}$$

where p_x is the probability of a state x and ENS_x is the ENS in that state. Assuming each day of historical data to have an equal probability of occurring, then the expected energy not supplied per calendar year is given by:

$$EENS = \frac{365}{n} \cdot \sum_{x=1}^{n} ENS_x \tag{10}$$

Because electricity demand and line ratings vary throughout the year, the calculations are performed on a per-season basis; the final EENS is then calculated as a weighted sum of the seasonal calculations, with weightings based on the length of the season according to UK DNOs [18].

$$\begin{aligned} EENS = \frac{3}{12} EENS_{\mathrm{win}} + \frac{2}{12} EENS_{\mathrm{spr}} \\ + \frac{4}{12} EENS_{\mathrm{sum}} + \frac{3}{12} EENS_{\mathrm{aut}} \end{aligned} \tag{11}$$

Fig 4 shows examples of this method. In the top figure, (a), the network capacity is sufficient, so there is no need for the ESS to deliver energy. In (b), the network capacity is not sufficient to meet the demand, so the ESS makes up the shortfall; because the ESS has sufficient power and energy, there is no ENS. Finally, (c) shows a day on which the network capacity is insufficient, and the ESS does not contain enough energy to make up the shortfall; in this case, there is an ENS value of ~5 MWh at the end of the day. The examples shown are only illustrative; the MC method relies on a substantial dataset, and many repetitions of these calculations.

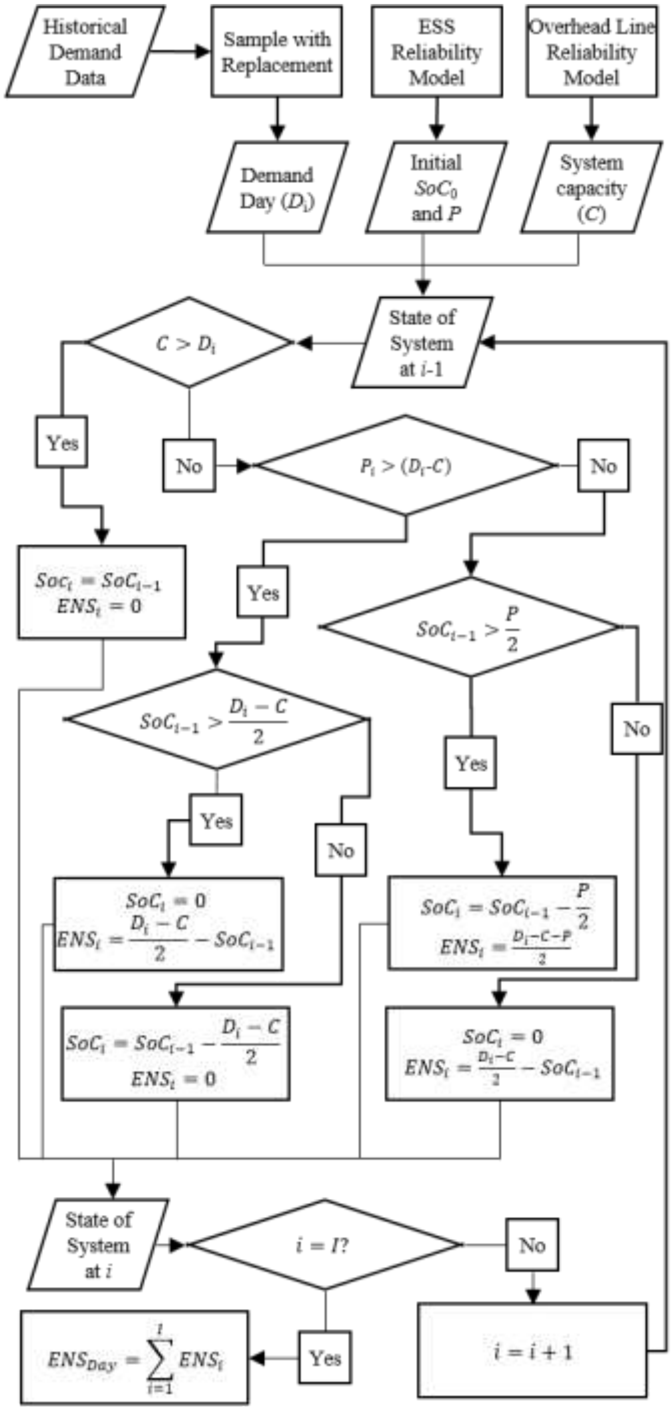

Fig 3. The algorithm used to assess the EENS. SoC_i refers to the state of charge at the end of time step i, ENS_i is the energy not supplied in time step i, I is the number of time steps in a day and P is the power rating of the ESS

B. Demand Growth

Investments in power systems need to be taken with long-term consequences in mind. New assets will often be in place for at least 30 years, so any problem they are installed to mitigate should be dealt with throughout their operational lifetime. While smart grid interventions do not always have the same lock-ins and high costs as conventional network reinforcements, an ESS scheme will still be expected to operate for around 10 years (a lithium-ion battery has a lifetime of approximately 3000 complete cycles [23]). Consequently, it is important to see how the impact of the ESS will change with demand growth. In this paper, demand growth was modelled as increasing at a rate of 1%/year without compounding. Consequently, the demand in year 10 was 10% higher than the base demand case.

C. ESS Utilization

It is unlikely that installing ESS for a single purpose, peak shaving in this case, would be economically justified. An ESS project will need to participate in ancillary services and arbitrage to compete with conventional reinforcement. Consequently, the hours per year spent fulfilling the primary peak shaving function determine the economic viability of the ESS – this includes being on standby, even though, in the majority of cases, it will not be required to supply power.

D. Network Capacity and Real-Time Thermal Ratings

In this paper, an RTTR system is modelled to investigate whether the combination of RTTR and ESS is advantageous. There are four potential consequences to be evaluated:

- The increased network capacity through using RTTR decreases the size of the required ESS
- The ESS is required for PS less frequently
- The presence of the ESS decreases the network risk during low rating events
- RTTR extends the deferral of conventional reinforcement originally provided by ESS

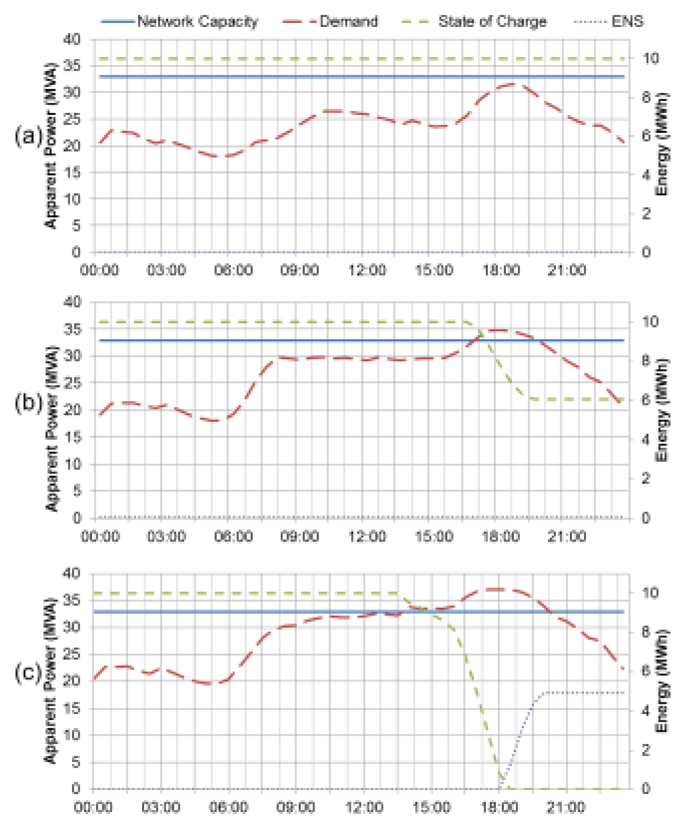

Fig 4. An illustration of how the method works in three different scenarios. In (a) there is no need for peak shaving. In (b), there is a need for peak shaving, and this energy is taken from the ESS. In (c) there is a need for peak shaving, and the total required energy is greater than the ESS capacity, so the ENS value is non-zero by the end of the peak.

Example data, showing the demand and line ampacity over the course of 4 winter days, is shown in Fig. 5; this data illustrates the significant events that can occur when using RTTR in conjunction with ESS. In the first day, the ampacity of the conductor drops below the static rating. This will reduce the network capacity available for charging an ESS, but demand is below both ratings at all times so no PS is required. On the third day, the peak demand is greater than the static rating, but less than the RTTR. This means that PS would be required if the true rating of the conductor was not known. On the fourth day, the RTTR drops below the static rating and the demand. This means that PS will be required at an unusual time of day and, without RTTR, the network would potentially be unsafe without the operator's knowledge.

The methods described in section IIIA require little modification to account for RTTR. A day of rating data, from a database whose size is of the same order as the demand database, is sampled with replacement and, rather than using a fixed network capacity, the appropriate value from the sampled line rating data is used at each time step. The simulations are still performed per-season, with only weather data from the appropriate season being used to calculate the ratings for simulations within that season.

III. Case Study

A. Electricity Demand Data

The demand data for this study is taken from a 33/11kV substation in the East of England. The substation is the site of UK Power Networks' Smarter Network Storage (SNS) project [2], which is providing security of supply by using an ESS for peak shaving, together with gaining revenue by participating in commercial services. Historical half-hourly demand data was available for 2008-2014. Fig 6 shows the likelihood of different levels of demand at each half-hour period during a day in each season.

For the given historical data, with a 60°C line thermal limit, the peak shaving would be required on approximately 5% of spring and autumn days, and 10% of winter days. With a 50°C line thermal limit, the peak shaving would be required more frequently, and greater quantities of both power and energy would be needed. A more detailed discussion of line limits and their underlying assumptions can be found in [16].

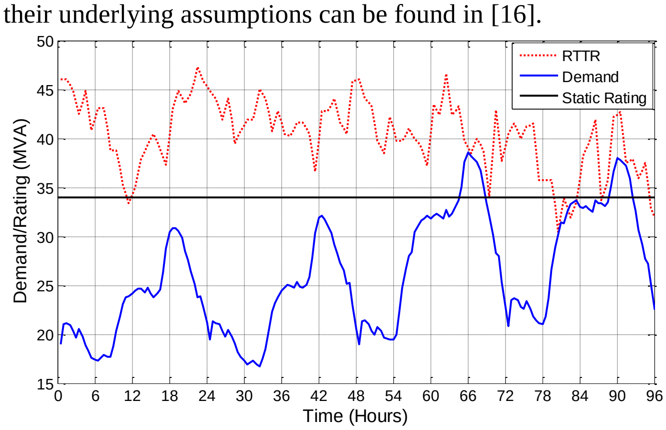

Fig. 5. Time series of Real-Time Thermal Rating (RTTR), Static Rating and Demand for a 4 day period

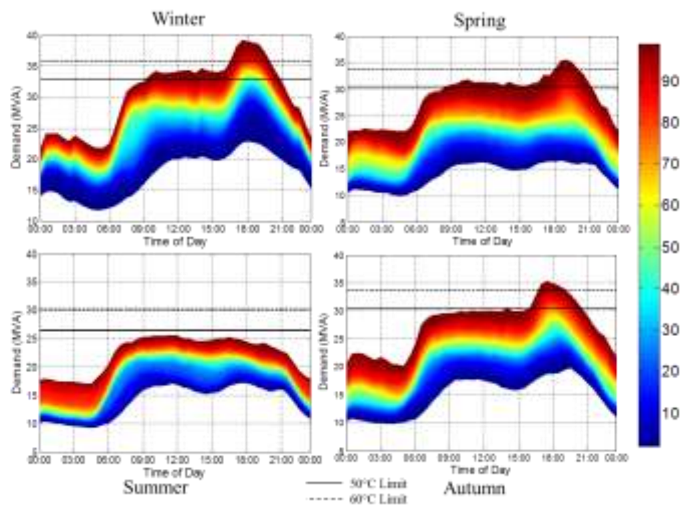

Fig 6. Demand cumulative probability plots for spring, summer, autumn and winter. The 50°C and 60°C thermal line limits are also shown, to give an indication of the level of peak shaving that is required.

B. Substation topology

The data in Fig 6 suggest that customers at the substation are disconnected on a regular basis to ensure that the line's thermal limits are not infringed. This is not the case; distribution networks are required to have sufficient redundancy such that large demand groups are rarely disconnected (Engineering Recommendation P2/6, which serves as a security of supply standard, ensures that this is the case in the UK [24]). Consequently, the substation in question is supplied by two incoming OHLs, the thermal limits of which are shown in Table I. The local network topology is shown in Fig 2.

TABLE I
THE THERMAL LIMITS OF THE OHLS AT THE SUBSTATION

	50°C Limit (MVA)	60°C Limit (MVA)
Winter	32.9	35.8
Spring/Autumn	30.5	33.8
Summer	26.4	30.2

C. RTTR Data

For this paper, RTTR was calculated using the method described by [5]. Hourly wind speed and temperature observations were available for 2011-2014, via the British Atmospheric Data Centre [25]. Linear interpolation was used to convert this to half hourly data, for consistency with the demand data. Wind direction and solar radiation were both assumed to be zero (for wind direction this means flow parallel to the line), since these vary too much on relevant space scales to be accounted for. These are the same assumptions used in line rating standards [26]. CIGRÉ [27] OHL rating equations were used to calculate line ampacity.

IV. Results

A. Selecting Power and Energy Capacity

The method described in section II is used to estimate the EENS corresponding to an ESS with a specific power and energy rating. The method was used to evaluate ESS devices with energy capacities ranging from 1-20 MWh and power ratings ranging from 1-10 MW. The OHLs and ESS were assigned availabilities of 99% and 95% respectively. Demand was increased to show the impact of the ESS from the base case to 10 years in the future; the EENS is shown in Fig. 7. These results can be used to establish a lower bound for the ESS power and energy ratings, with the decision on what constitutes acceptable EENS left to the operator's discretion.

Increasing the power rating of the ESS initially reduces the EENS, but once the power rating reaches 4 MW the EENS levels out, increasing slightly as demand grows. The energy capacity also improves the EENS, but for the present day scenario the benefits begin to tail off once the capacity reaches 10 MWh. However, in future scenarios the EENS is still falling with 20 MWh of ESS. A base level of EENS (around 20 MWh/year for the base case) remains throughout the simulations; this is a consequence of a double circuit outage, in which the ESS cannot prevent customer disconnections.

B. The impact of ESS reliability

The results in Fig. 7 assumed the ESS was available on 95% of days. In reality, ESS may be more or less reliable than this. The simulations for the present day case and for year 10 were re-evaluated, varying the availability of the ESS from 1 to 0.9. In a real system, the reliability is likely to be at its lowest during the beginning and end of the system's life [28]. Fig. 8 shows the result of changing the availability, for year 10; Table II shows the capital cost for each ESS considered for Lithium Ion batteries [29].

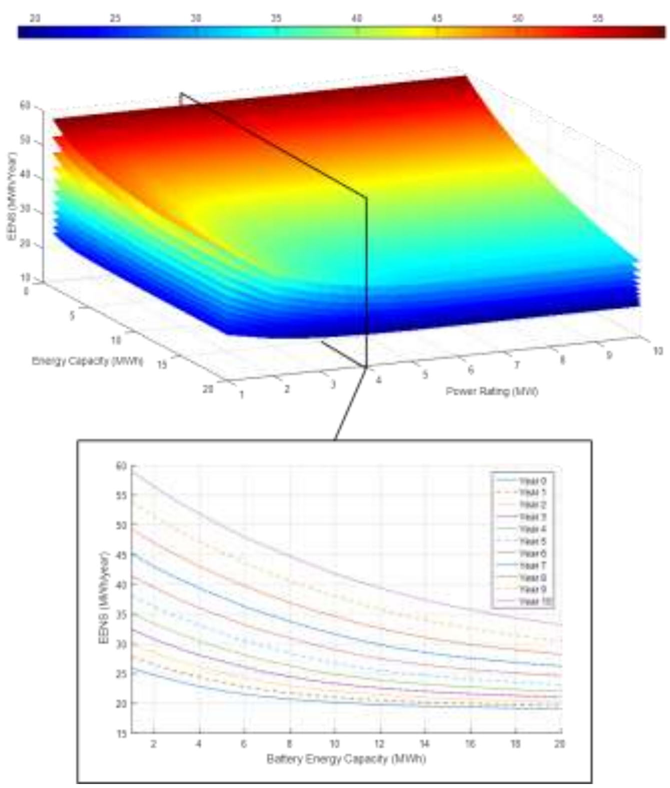

Fig. 7. Top – Surface plots of EENS for ESS with power ratings from 0-10 MW, energy capacities from 0-20 MWh and demand increasing from the present case to ten years in the future, with ESS availability of 95%. Bottom – Line graphs of EENS against energy capacity for a power rating of 4 MW.

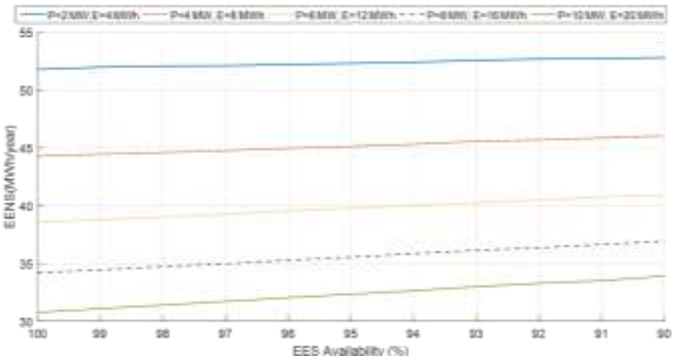

Fig. 8. The impact of reducing ESS availability on EENS for a variety of ESS systems in the year 10 demand scenario

Initially, increasing the size of the ESS has a greater impact on EENS than increasing its reliability; even a perfectly reliable 2 MW/4 MWh system gives a higher EENS than a 4 MW/8 MWh system with an availability of 90%. However, as the ESS reaches the sizes suggested by the results in section A, the availability starts to have a significant impact; a 8 MW/16 MWh system with availability of 100% is approximately as effective at providing security of supply as an 10 MW/20 MWh system with 90% availability.

C. Storage Sizing with RTTR

The sizing study was repeated, replacing the static line ratings with RTTR. Fig. 9 shows an equivalent multi-surface plot to Fig. 7; the base EENS remains unchanged but the EENS for a given size of ESS is lower, particularly in the case of smaller ESS.

The EENS also increases less as the demand grows, with the 4 MW/10 MWh system resulting in around 27 MWh/year rather than 42 MWh/year with only the ESS (Fig. 7). Fig. 10 shows the investment deferral achieved by installing RTTR, a 6 MW/10 MWh ESS or both. If we assume that a slight reduction based on the existing level – 40MWh/year - is the maximum acceptable level, neither the ESS nor RTTR defer the investment for the full lifetime of the project. However, the combination of RTTR and ESS defers it by at least 10 years, with a substantial reduction in EENS compared with either technique used in isolation.

D. Utilization of ESS for Peak Shaving

A combination of RTTR and ESS will allow the existing system to maintain the present reliability level for 9 years of 1% demand growth. The ESS business case is based on combining network reliability and participation in commercial

TABLE II
THE CAPITAL COST OF ESS

	Converter Costs ($M)	Battery Costs ($M)	Total ($M)
2MW/4MWh	1.8	3.3	5.1
4MW/8MWh	3.6	6.5	10.1
6MW/12MWh	5.4	9.8	15.2
8MW/16MWh	7.2	13.1	20.3
10MW/20MWh	9.0	16.3	25.3

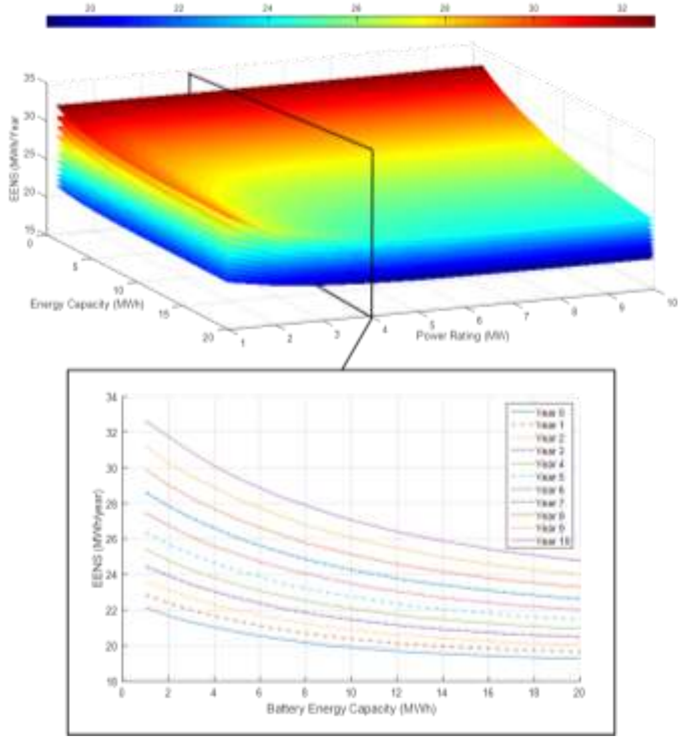

Fig. 9. Top – Surface plots of EENS for the combination of RTTR and ESS with power ratings from 0-10 MW, energy capacities from 0-20 MWh and demand increasing from the present case to ten years in the future, with an ESS availability of 95%. Bottom – Line graphs of EENS against ESS energy capacity for a power rating of 4 MW.

services. Whether the ESS is used alone, or alongside RTTR significantly affects shows the proportion of time that the ESS will be needed to provide security of supply. In Fig. 11, this utilization has been calculated for the existing demand and the demand following 10 years of demand growth, considering systems using static rating and RTTR. The results show that the use of RTTR reduces the number of hours per year that the ESS must be available for peak shaving – and would be called on if a single circuit outage occurs.

Because the peak shaving is concentrated in winter and autumn, the ESS could be made available for commercial operation for entire weeks or months during summer – though only if it is being operated alongside RTTR. An alternative viewpoint is to say that lower utilization of the ESS will extend its operational life, so by combining RTTR and ESS we can extend the operational use of the ESS and defer further reinforcement for longer.

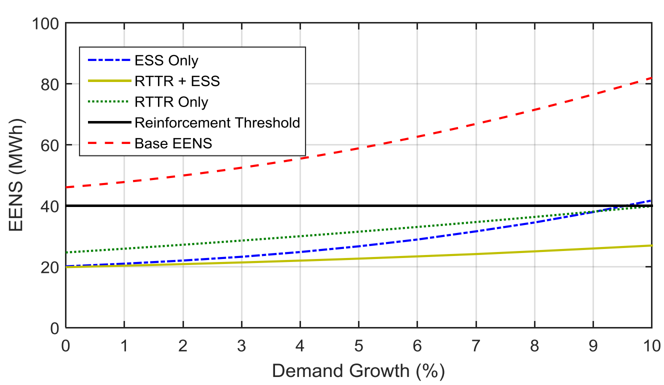

Fig. 10. The impact of storage and RTTR on EENS with demand growth. This figure considers 6 MW/10 MWh of ESS with 95% availability

E. Economic Analysis

An economic analysis – comparing reinforcement via ESS with conventional, asset based, reinforcement – is multi-faceted and site specific. The feasibility of implementing an ESS to provide security of supply, at a competitive cost compared with conventional reinforcement, depends on a number of factors:

- The cost of the storage system – including land, storage medium, converter technology, connection, buildings and operation. The storage medium makes up the majority of this cost, but prices are falling, particularly in the case of Lithium Ion batteries [30]
- The cost of conventional reinforcement – this primarily depends on the distance from the primary substation to the grid supply point. In addition, there is a time consuming planning process, which means that the conventional reinforcement would generally take longer to construct that an ESS, which must also be factored into the assessment.
- The value of additional revenue from ancillary services – Even with the reduction in cost for ESS technology, it is likely that an ESS solution has greater capital costs than conventional reinforcement. However, ESS can provide additional revenue – through commercial opportunities such as energy arbitrage and Triad, and grid balancing services such as frequency response and operating reserve – and additional value to the distribution network – through voltage control or reactive power compensation. Quantifying the value of these benefits over the lifetime of these services is not straightforward, but an estimate can be made based on the utilization calculated in section IV.D. Combining the peak-shaving function with one or more commercial services requires robust management of the ESS's power and energy resources. To provide this, a forecasting, optimization and scheduling system has been developed as part of the SNS project [31].

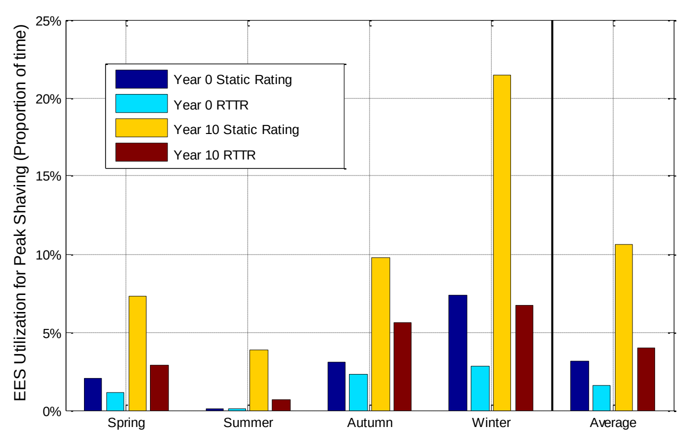

Fig. 11. ESS utilization for peak shaving with static ratings and RTTR, in the initial demand case and the year 10 demand case

An example economic assessment is presented here. The value of the ESS is considered as a function of life cycle costs over an assumed 10 year lifetime, ancillary service revenues and reliability savings. The value of the ESS is considered with and without RTTR. The lifetime value, V is calculated as:

$$V = R_{\mathrm{PS}} + R_{\mathrm{AS}} - C_{\mathrm{LC}} \quad (12)$$

where R_{PS} is the saving from peak shaving, R_{AS} is the revenue from ancillary services, and C_{LC} is the lifecycle cost. The lifecycle cost was calculated using the average data in Table III and the following equation [29].

$$C_{\mathrm{LC}} = P.(PCS + L.FOM + RC) + E.(SS + L.VOM) \quad (13)$$

PCS is the capital cost of the power conversion system, *SS* is the capital cost of the energy storage medium, *FOM* and *VOM* are the fixed and variable operation and maintenance costs respectively. P and E are power rating and energy capacity respectively. The results shown assume a lifetime, L, of 10 years.

The peak shaving revenue, R_{PS} was calculated using the EENS results from section IV.A.

$$R_{PS} = \sum_{y=0}^{Y} EENS_y . VOLL \quad (14)$$

where EENS_y is the loss of energy expectation for year y, and *VOLL* is the value of lost load – in the UK, VOLL is approximately £16940 ($25060) per MWh [32].

We considered Frequency Response (FR) as the main ancillary service activity; FR revenue is calculated using:

$$R_{\mathrm{AS}} = \sum_{y=0}^{Y} (8760 - 2.PSH_y).FRV.min\begin{cases} P \\ \frac{E}{2} \end{cases} \quad (15)$$

where *PSH* is the number of hours required for peak shaving in a given year and *FRV* is the value of the value of the frequency response service in $/MW/h – for this paper we have assumed a value of $16. The more valuable FR services require delivery in both directions, requiring the ESS to operate at approximately 50% state of charge. In the UK, the maximum delivery would be 15 minutes at full power [33], which gives a maximum power:energy ratio of 2:1; this is represented by the minimum term in equation (15).

When RTTR is included, the capital cost of RTTR is estimated at $17000/km [34]; the overhead lines at the case study site are 11 km long, so the cost of RTTR is $187000.

TABLE III
COMPONENTS OF ESS LIFECYCLE COST [29]

Cost item	Average	Middle fifty range IQR	Range
PCS (€/kW)	463	398–530	241–581
Storage section (€/kWh)	795	676–1144	470–1249
Fixed O&M (€/kW-yr)	6.9	4.9–11.2	2.0–13.7
Variable O&M (€/MWh)	2.1	0.99–3.6	0.4–5.6
Replacement costs (€/kW)	369	284–505	187–543

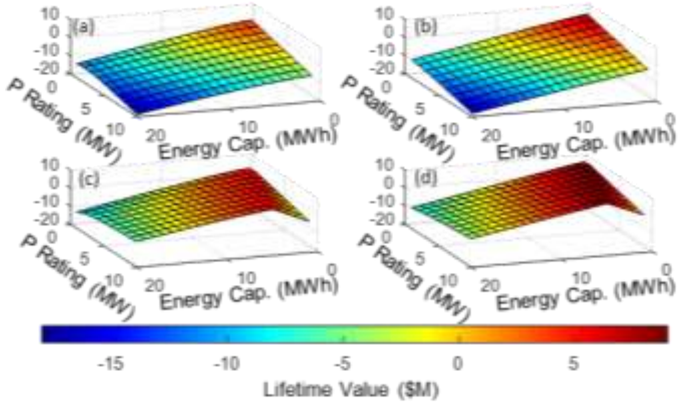

Fig. 12. Surface curves showing the estimated lifetime value of energy storage with different power and energy ratings. (a) shows the value of an ESS performing only PS; (b) shows the value of an ESS and RTTR performing PS; (c) shows an ESS performing PS and FR, and (d) shows an ESS and RTTR performing PS and FR.

The lifetime value of ESSs, varying from 1MW/1MWh to 10MW/20MWh was calculated, and the results are shown in Fig. 12. Results were calculated with and without RTTR, and with and without participation in FR; the results suggest that RTTR significantly increases the lifetime value of any system. There is a diminishing return in the size of the ESS needed to fulfill PS, since additional capacity will only be used in larger PS events, but it is nevertheless required for security of supply. The FR income makes a substantial difference to the design of the ESS; while the value of the system decreased with both additional power and energy capacity in both static and RTTR cases without the FR revenue, once it is included there is a clear incentive to maximize the power capacity (up to 2C), of any ESS participating in frequency regulation.

Without participating in FR, the optimal system would be the smallest configuration that adequately provides security of supply. Once FR is added as a revenue stream, there is still an incentive to minimize the energy capacity, but to provide sufficient energy conversion to allow operation at 2C. This could influence which battery technology is best suited to the application.

V. Discussion

The methods and results presented in section IV are valuable steps forward for ESS in distribution networks. This section discusses their implications from technical, commercial and regulatory perspectives.

A. Technical Implications

The results presented in this paper give some indication of how ESS, RTTR and the combination of the two can improve distribution network security of supply. For the example system, increasing the power rating of the ESS only provided benefits up to around 4 MW, while the energy capacity continued to provide improvements up to 20 MWh. The addition of RTTR proved more beneficial in a load growth scenario, because the demand is likely to be above the static rating for a greater proportion of the time. RTTR also reduces the utilization of the ESS for PS, either freeing it to perform more commercial services or extending its operational lifetime. This extension is particularly useful given that the combination of RTTR and ESS is found to solve a network problem for considerably longer than either would in isolation.

There are, however, technical challenges to be overcome before the full benefits identified in this paper can be realized. The most effective utilization of ESS requires the quantity of energy required at each point in time to be known in advance. Consequently, the effectiveness of this solution will hinge on accurate forecasting of both the demand [1] and the network ratings [35]. Second, it is likely that the ESS will be required to perform other services; optimizing the system for these could affect the power and energy requirements (e.g. relatively high power/low energy frequency services). The method presented in this paper could be used to size the proportion of an ESS required to perform PS, with additional capacity available to participate in commercial services with a high level of confidence that it will not be required for PS.

B. Regulatory and Commercial Implications

The research in this paper has demonstrated that a combination of ESS and RTTR can reinforce distribution networks in place of conventional asset-based reinforcements. However, the existing network regulations in the UK and elsewhere are not set up to recognize this alternative, and should consider using the methods in this paper to provide a framework for quantifying the benefits. Existing methods based on firm capacity [36] are not well suited to accommodating either RTTR or ESS. Increased cost efficiency could be realized by use of probabilistic, risk based methods, as has been presented here.

A full economic appraisal of these systems would make use of this method to provide network performance data. This would allow a comparison with the costs and benefits of alternative solutions, expansion or replacement of existing assets. Although we have presented directly applicable results, this full economic assessment is beyond the scope of this paper, since it depends on many factors other than the ESS and RTTR systems.

As discussed earlier, an ESS is likely to participate in commercial network services when it is not providing the PS service. Many of these services are currently set up for the participation of generators, from which ESS differs in several fundamental respects. Creating a new market specifically for storage, or altering the terms to allow storage to more meaningfully participate, may be required to incentivize the wide scale adoption of ESS. Further to this, in the UK, existing network regulations make it difficult for distribution network operators to own and operate storage. Consequently, if ESS is considered a favorable means of reinforcement within distribution networks then the regulation must change to either allow DNOs to operate storage in this context, or, to set a framework for third party ESS operators to offer PS contracts to DNOs [37], perhaps as part of a distribution network ancillary service market.

VI. Conclusion

This paper has described a new method for assessing the appropriate size of ESS for a demand peak shaving application to enhance distribution network security of supply. This method takes account of the variability of demand, power and energy limits, and ESS reliability. Results, from the site of a real ESS trial in the UK, suggest that increased energy capacity has a greater impact on EENS than power conversion system rating. Additionally, the impact of ESS reliability becomes a significant factor once the ESS reaches a sufficient size to trim the majority of demand peaks.

Additionally, this paper contains the first research to quantify the combined benefits of ESS and RTTR on distribution network security of supply. By extending the sizing method to include RTTR, we obtain results which show that the combination of the two technologies not only provides a greater benefit to security of supply than either individually, but also results in lower utilization of the ESS for the primary peak shaving function, allowing it to participate in additional commercial service markets or provide lifetime extension. Using our results, we demonstrated that RTTR increases the value of an ESS, and that a substantially different power:energy ratio is desirable for a single function, vs for multiple functions.

Finally, the technical and regulatory requirements that stand in the way of realizing these benefits were discussed, and possible approaches to remove these barriers put forward.

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