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Design and analysis of electrical energy storage demonstration projects on UK distribution networks

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Abstract— The UK government's CO₂ emissions targets will require electrification of much of the country's infrastructure with low carbon technologies such as photovoltaic panels, electric vehicles and heat pumps. The large scale proliferation of these technologies will necessitate major changes to the planning and operation of distribution networks. Distribution network operators are trialling electrical energy storage (EES) across their networks to increase their understanding of the contribution that it can make to enable the expected paradigm shift in generation and consumption of electricity.

In order to evaluate a range of applications for EES, including voltage control and power flow management, installations have taken place at various distribution network locations and voltage levels. This article reports on trial design approaches and their application to a UK trial of an EES system to ensure broad applicability of the results. Results from these trials of an EES systems, low carbon technologies and trial distribution networks are used to develop validated power system models. These models are used to evaluate, using a formalised methodology, the impact that EES could have on the design and operation of future distribution networks.

Highlights:

- Results of an EES system demonstration project carried out in the UK
- Approaches to the design of trials for EES and observation on their application
- A formalised methodology for analysis of smart grids trials

- 29 • Validated models of energy storage
- 30 • Capability of EES to connect larger quantities of heat pumps and PV is evaluated

31 **Keywords—** Electrical Energy Storage, Distribution Networks, Field Trials, Smart Grid

32 Nomenclature

33	ASHP	Air-Source Heatpump
34	AVC	Automatic Voltage Controller
35	CO ₂	Carbon Dioxide
36	CLNR	Customer Led Network Revolution
37	DG	Distributed Generation
38	DNO	Distribution Network Operator
39	EES	Electrical Energy Storage
40	EOL	End of Life
41	EPSRC	Engineering and Physical Sciences Research Council
42	EV	Electrical Vehicle
43	LCT	Low Carbon Technology
44	LCNF	Low Carbon Network Fund
45	NOP	Normally Open Point
46	OLTC	On-Load Tap Changer
47	PCC	Point of Common Coupling
48	PV	Photo-voltaic
49	SOC	State-of-Charge
50	SOH	State-of-Health
51	UKPN	United Kingdom Power Networks
52	UK	United Kingdom
53	VEEEG	Validation, Extension, Extrapolation, Enhancement, Generalisation
54	VSC	Voltage Source Converter

1. Introduction

The forecast electrification of key UK infrastructure such as heat and transport required by the UK government's aggressive CO₂ targets will result in major changes to the planning, design and operation of the UK's electrical infrastructure. This paper describes research undertaken by projects funded by the UK energy regulator's (Ofgem) Low Carbon Network Fund (LCNF) and the Engineering and Physical Sciences Research Council (EPSRC) in response to these expected changes. A trial of electrical energy storage (EES) has been carried out by UK Power Networks (UKPN), ABB, Durham University and Newcastle University to develop realistic models of a real EES system and to enable evaluation of the use of EES on future distribution networks. This project was originally part of the AuRA-NMS Strategic Partnership between the EPSRC, Scottish Power Energy Networks, ABB and UKPN (formerly EDF Energy Networks) [2, 3]. Subsequent work, focussing on the deployment of the EES system, was the first project to register in the LCNF as a First Tier project [4, 5]. The validated network, customer load and LCT models described in this work are derived from the Customer Led Network Revolution (CLNR) project programme [6] again funded by Ofgem's LCNF. This is the UK's largest smart grid project thus far with metering data from over 20,000 industrial, commercial and residential customers as well a smart grid trial programme of over 87 smart grid interventions.

In this work these realistic load, generation, network and EES models are used collaboratively to evaluate, using a formalised methodology, the impact that EES could have on future distribution networks. This formalised methodology can be used to evaluate the capability of these networks, equipped with EES or other advanced interventions, to connect the anticipated large scale proliferation of LCTs. This approach will enable DNOs to make more informed network planning, design and operational decisions based on a combination of realistic models based on trial results.

2. Background

The projected increase in customer demand, due to the proliferation of EVs and heat pumps, and much higher levels of zero-carbon intermittent renewables based generation to distribution networks will present major challenges to DNOs in terms of voltage control and powerflow management [7, 8]. Grid connected energy storage can provide a variety of network services, including voltage control and powerflow management, in future electrical power systems [4, 8-25]. These can be summarised as follows:

- *Voltage control*: Support heavily loaded feeders, power factor correction, reduce generator curtailment, minimise on-load tap changer (OLTC) operations, mitigate flicker, sags and swells [4, 17-19, 26];

- 81 • *Power flow management*: Defer network reinforcement, reduce reverse power flows, reduce generator curtailment,
82 reduce losses [4];
- 83 • *System Restoration*: Voltage control and power flow management in a post fault network [10]
- 84 • *Energy/ancillary markets*: Energy arbitrage, balancing market participation, reduce intermittent generation
85 variability, increase intermittent generation yield from non-firm connections [4], provide ancillary services
86 (frequency response/operating reserves) [27];
- 87 • *Commercial/regulatory*: Assist in compliance with energy security standard (ER P2/6) [28], reduce customer minutes
88 lost, reduce generator curtailment [4, 10];
- 89 • *Network management*: Facilitate islanded networks, support black starts, switch EES between alternative feeders at a
90 normally open point (NOP) [4].

91 However, the adoption of grid-connected energy storage within electrical power systems has been hampered by technology
92 costs, limited deployment experience, existing electricity market and regulatory structures and complex value chains which
93 increase investment risk [25]. To mitigate against these issues a number of assessment techniques have been developed.

94 Comparative, techno-economic analytic assessments of the capability of energy storage to participate in energy arbitrage,
95 frequency regulation, managing short-term fluctuations, and standing reserve are described in [21, 23, 29-31]. Economic
96 assessments of the use of energy storage to increase the energy yield of and reduce the generation uncertainty associated with
97 stochastic energy sources, by using it as an energy buffer, have been extensively evaluated [32-34]. Sophisticated modelling of
98 economic or financial scenarios for energy storage is required to understand and determine the economic benefits of energy
99 storage in electrical power systems. However, it should be noted that these analytic methods do not require accurate modelling of
100 the dynamic operation of an energy storage system.

101 More detailed, dynamic models of energy storage, in electrical power systems, have been used extensively to evaluate the
102 increase in energy yield and reduction in generation uncertainty associated with stochastic energy sources, by using it as an
103 energy buffer [26, 35-41]. A filtering time constant is used to model the impact of energy storage on the input wind power data
104 in [35]. A year round evaluation of wind and energy storage system operation, using an hourly wind and demand time series and
105 a simple energy storage model is used to evaluate the value of energy storage in [42]. In [26], a model which accounts for
106 efficiency of energy storage is used to evaluate the capability of energy storage with reactive power control to minimise energy
107 loss and enhance voltage stability of an islanded system. In [41] a dynamic model of a wind turbine and flywheel energy storage
108 system model is used to evaluate its capability of wind power smoothing.

For voltage control, powerflow management, system restoration and network management, models that reflect the dynamic behaviour of an actual system are necessary to ensure that the resultant network design is not only economically feasible but is also technically acceptable. Steady-state load flow analysis of an electrical network model loaded with values from historical operational data sampled at 30-min intervals is used to evaluate the capability of energy storage to regulate voltage and manage powerflows in [4, 18, 19]. In this case the energy storage was modelled as an electrical load when charging and a generator while discharging. A similar modelling approach is applied to evaluate a strategy which integrates sophisticated control of an automatic voltage controller (AVC) with EES systems, to regulate voltage across a representative future distribution network, with large numbers of EVs, heat pumps, PV installations and a windfarm [17]. Optimised combinations of real and reactive power for voltage support and loss reduction were assessed using detailed dynamic models of the control scheme and a simple energy storage model [43]. These models however do not use the results of practical grid connected energy storage to inform the development of the models used.

This work demonstrates, using results from a trial of a grid connected EES unit that these models need to be carefully applied in analysis. These initial practical results indicate a more pessimistic assessment of the capability of EES to control voltages and manage powerflows is necessary. In addition, this work also indicates how large scale proliferation of load or generation LCTs will modify current load/generation profiles, which will in turn have significant impacts on the appropriate power rating and storage capacity of an EES system.

This paper reports on research that has addressed the need for the development of methods that will enable the benefits of EES systems to be assessed using a combination of appropriately designed field trials and relevant simulation and analysis. In the following section, the Hemsby EES installation and trial design approach is detailed. This is followed by a description of the formalised trial analysis methodology used to evaluate these trials. Results from the application of the trial analysis methodology on a peak-shaving trial carried out using the Hemsby EES system, is presented in the following section. The analysis enables evaluation of this and similar systems' capability to facilitate connection of heat pumps and PV generation and defer reinforcement in future distribution networks. The results are discussed cognisant of the practical issues observed along with the broader implications for the design and analysis of field trials of distribution network connected EES systems.

3. Field trial of energy storage at Hemsby

In addition to the energy storage system at Hemsby there are a number of UK demonstration projects with grid connected, operational EES systems; the Orkney Smart Grid, with an energy capacity of 500kWh; a 3MWh energy storage system in Shetland; the CLNR project, which features six units with energy capacities ranging from 100kWh to 5MWh; three units at

Chalvey with a capacity of 25kWh; and a unit deployed in Bristol with a capacity of 14.4kWh [44-48]. In addition, a compressed liquid air based energy storage, with an energy capacity of 2.4MWh has been commissioned [49].

The Hemsby EES system was designed and built by ABB. The installation is connected on an 11kV distribution network in the East of England. The EES consists of a 200kW/200kWh lithium-ion battery array, manufactured by Saft, coupled to ABB's SVC Light (a static VAr compensator) and control system [5]. This lithium-ion battery technology is designed to have calendar lifetime of 15 years, charge/discharge lifetime of 3000 cycles with 80% depth of discharge. The battery system was found to have round-trip efficiencies of between 90% and 95% measured [50]. However, auxiliary power consumption was found to have a significant impact on the system resulting in round trip efficiency that could be as low as 78%, depending on the amount of power exchange.

The EES has been placed at an NOP to allow connection to either one of two feeders fed from different primary substations as shown in Figure 1. The loads supplied by these feeders are a mixture of farming, light industrial, residential and holiday accommodation. A 2.25 MW windfarm with fixed speed induction generators is connected midway along one of these feeders.

Figure 1: Field trial network diagram (Windfarm is indicated by letter G)

4. Trial design methodology

As this is a demonstration project on a region of 11kV network operated by a UK DNO, the trial designs are designed to minimise disruption to the network and comply with the operational and safety requirements of the DNO's network [7, 51]. Management of voltage and powerflows have been identified as key objectives for control of smart grid network interventions [7]. The four-quadrant voltage source converter (VSC) enables independent control of real and reactive power import/export from the EES which is used to manage voltage and powerflows in the immediate distribution network [51]. At this installation, measurements at the Point of Common Coupling (PCC) of the ESS and remote locations (far end of the feeder or at a mid-point

towards the windfarm) can be used as input measurements to voltage control and powerflow management algorithms which can regulate the flows of real and reactive power flowing into/out of the EES [51].

The peak-shaving capability of EES is the focus of this investigation. To minimise the possibility of disruption to customers, the power capability of the EES was relatively small in comparison with the powerflows on the 11kV feeder. This necessitated changes to the operational limits and set points to ensure that the EES was regularly active in response to thermal events during the trial period. This provided a meaningful evaluation of the EES system characteristics and performance. A number of approaches have been previously identified to determine these changes [7]: -

1. Network element models held in control system are lower rated than reality;
2. Scale thermal/current ratings of infrastructure elements;
3. Reconfiguration of the network (N-1, N-2 conditions) to increase powerflows;
4. Scaling of results from monitoring systems prior to their submission to control system.

As the daily and seasonal variability of the 11kV feeder powerflow would result in either limited or frequently saturated operation of the EES system, a variant of option 1, with additional functionality in the peak-shaving algorithm of the Hemsby EES systems, was used [51]. The additional algorithm functions were as follows:

1. If the EES system real power import/export exceeded 60kW, any further increase in the margin above the threshold resulted in an increase of real power import/export equal to 10% of the margin. This limits the allowable power exchange level. Although the Hemsby EES is capable of 200kW, this rule limits the power below 100kW to preserve the (200kWh) energy capacity.
2. Adaptive peak-shaving. This is illustrated in Figure 2.

Figure 2: Flow chart of adaptive peak shaving algorithm

The adaptive peak-shaving algorithm monitors and stores historical time and magnitude of peak power flow occurring on the feeder. The algorithm uses this data to predict the daily load curve and thus determine the appropriate switching time windows and trigger levels for each day that ensures that, the battery energy resource is used in a way that will maximize the usage of the ESS during the trials [5]. A flow chart illustrating the overall EES control algorithm is presented in Figure A.1 in Appendix A.

5. Post-trial analysis methodology

The formalised post-trial analysis methodology known as VEEEG (Validation, Extension, Extrapolation, Enhancement, Generalisation) has been applied to the peak-shaving field trial results from Hemsby. This methodology, illustrated diagrammatically in Figure 3, ensures that the results smart grid trials are systematically analysed to provide robust findings with broad applicability [7]. This methodology has been developed previously as part of the CLNR project programme [6] and is developed here as a generalised approach to analysing smart grid trials.

The methodology uses the smart grid trial results to validate the network and network component models. The results from the trials are then expanded and augmented to fully explore the capability of a smart grid network intervention or combinations of smart grid interventions, to contribute to network operation in future distribution networks.

Figure 3: Post-trial analysis methodology

Validation

Pre-trial models of the local power systems and the smart grid systems are completed in order to build confidence in the operation of the field trials and ensure that the deployed systems will operate as required and maintain system operation within limits. In order to complete the later phases of the methodology, accurate models of distribution network(s) and smart grid intervention(s) are required, therefore it is necessary to validate the pre-trial models with results from appropriately designed field trials and where necessary modify the models to produce post-trial models [7].

Extension

Due to operational and financial limitations, field trials carried out within a field trial programme will always be of limited duration. Trials may need to be extended in time, using the validated models, to evaluate the operation of the system over a

longer period to enable a more comprehensive evaluation of the application of the smart grid intervention. Moreover in this phase, trials which could not be completed, for unforeseen reasons, or trials that are not practically feasible can be simulated using the validated models [7].

Extrapolation

In this phase, trial results are extrapolated by modelling increased penetrations and/or relocation of LCTs, to evaluate future LCT take up scenarios on the trial networks. LCT models used within the future predicted scenarios can be derived from analysis of smart meter data, detailed monitoring surveys or relevant literature. Evolving load and generation patterns and LCT penetration growth will impact on the capability of distribution networks to accept LCTs and determines the optimal choices of smart grid network intervention combinations, customer tariffs or conventional reinforcement [7].

Enhancement

The enhancement phase enables evaluation of different sizes, new locations, new combinations and larger numbers of smart grid interventions on the study network(s). Actual trials are limited in terms of the location and number of interventions available [7].

Generalization

Where necessary generic load, generation and weather data will be implemented in simulation. In addition, if the study network is unrepresentative, other representative or generic networks can be used to generalise the results from the trial.

The methodology results in large numbers of options for analysis of a smart grid trial(s). Therefore, in applying this methodology appropriate choices, conscious of the final analysis objective, need to be made to ensure its efficient application. In the following section, the VEEEG methodology is applied to the peak-shaving trial at Hemsby.

6. Trial results and validation

6.1. Field trial results for peak-shaving

The effect of the peak-shaving algorithm, described earlier, in conjunction with EES in reducing powerflows on the 11kV feeder is illustrated in Figure 4. It can be seen that although operating as intended, due to the scale of the EES relative to the feeder demand, the effect of the EES system on the load profile is relatively small.

Figure 4: 11kV feeder powerflows with and without peak-shaving enabled (7th August 2013)

The operation of the EES and the impact that this operation has on the estimated SOC (State-of-Charge) of the battery is illustrated in Figure 5. During the morning charge period the estimated SOC increases from 32.5% to 80%. During the evening discharge period the estimated SOC dropped from 80% to 20% and then, following the reduction in the export of real power to zero, increased by 10% and reached a steady-state value of 30% after 25 minutes.

Figure 5: Real power import/export and SOC of EES system (7th August 2013)

This is due to the SOC estimation technique adopted by the system at Hemsby which uses the battery terminal voltage method [52]. However, when estimating SOC under dynamic conditions, when the battery is charging or discharging, there is a significant voltage drop due to the internal impedance, whereas when export power is reduced to zero, there is no current flow in the battery circuit and no voltage drop. Charging/discharging rates [53], battery age, state of health (SOH) [54] and environmental conditions (e.g. ambient temperature) also has been shown to have significant impact on this internal impedance value [55]. Consequently, the instantaneous online SOC estimator is significantly lower at the end of discharging than the no-load measurement (as shown in Figure 4). However, it should be noted that these observations vary depending on the level of power exchange prior to dropping to zero.

Other SOC estimation techniques such as internal impedance [56], open circuit voltage [57, 58], coulomb counting [59], artificial neural networks (ANN) [60, 61] or fuzzy logic [62, 63] have been reported.

When using the internal impedance technique information on the battery state of health (SOH) [52], charging/discharging current [53] and ambient temperatures are required. If this technique is applied, a wide range of impedance experiments are needed to carry out SOC estimation.

Coulomb counting calculates battery SOC by integrating the charging/discharging current over time with adjustments for the rate of charge or discharge of the battery [53, 64]. It requires few battery specifications and is easy to be implemented. However,

this technique is prone to estimation drift due to the integrating approach of this technique and over time could result in overcharging or undercharging of the EES unit.

Artificial neural networks methods are applied in SOC estimation due to their good ability of nonlinear mapping, self-organization, and self-learning. In [60], the ANN based SOC indicator predicts the SOC using the recent history of voltage, current, and the ambient temperature of a battery. However, the accuracy of ANN based SOC prediction is determined by availability of comprehensive historic data.

Fuzzy logic method provides a powerful means of modelling nonlinear and complex systems. In [62], a fuzzy-based method of estimating SOC of a battery system using data obtained by impedance spectroscopy (AC impedance). However, this fuzzy method is based on expert knowledge and may not be a generic method for all kinds of battery because impedance spectroscopy is dependent on material, manufacturing and environmental conditions.

In this work, models of both the SOC estimation algorithm and the battery system are required as these devices directly determine the capability of the energy storage unit to manage powerflows. However, efficient development of these models is restricted by:

1. Commercial sensitivities around battery parameters and performance and the SOC estimation algorithm used in an installation;
2. Complex models of battery systems and SOC estimation algorithms are difficult to implement in power systems modelling tools and can lead to large increases of computing time.

Therefore in this research, the coulomb counting method is adopted to estimate battery SOC within the model as it results in faster simulation times and also is accurate where the simulation is over a period of a few battery cycles. In addition, for energy exchange counting purpose, it is a generic method which is suitable for all kinds of battery system. It should be noted however that the method adopted is applied conservatively to reflect the operation of the energy storage system deployed as part of the trial.

6.2. System Modelling

In order to complete this assessment, detailed model of the Hemsby 33kV and 11kV network and the case study 11kV and LV networks have been developed in IPSA2 and validated against the field trial results from the Hemsby and CLNR projects respectively. The Hemsby distribution network model includes detailed models of the conductors and transformers from the 33kV connection point to the electrical location of the EES. The case study model includes a detailed model of the 20/0.4kV transformer and the downstream LV network. This approach, enabled by scripting of IPSA2 with Python, provides flexibility in

the time resolution used in the analysis. Previous studies use SCADA based data, with 30-minute times resolution [17] but in this case this more detailed analysis uses mostly 1-minute data where possible. The energy storage is modelled as an electrical machine which can either import or export real and reactive power to the network within the rating of the actual system. As per the Hemsby EES system reactive power is limited by rating only and not by duration, however real power is limited by the rating of the system and the calculated SOC of the battery and any limits imposed by the control algorithm. The control of the Hemsby energy storage system, described earlier, is implemented in Python enabling efficient interaction with the IPSA2 based power system models.

6.3. Validation

Pre and post-trial models of the EES and control systems have been developed. A comparison between the post-trial model and the field trial results for real power import and export is presented in Figure 6.

Figure 6: Comparison between Post-trial simulation EES model and EES real power export during discharge period (7th August 2013)

It can be seen that there is a good correlation between the results although there are some differences. The model does not take account of any latency in data acquisition for the control system or in implementing the control actions. It can also be seen that the discharge period lasts for longer in the model than in the real field trials. This is explained by comparison between the online SOC estimation from the trial and the model illustrated in Figure 7.

Figure 7: Comparison between post-trial simulation EES model and EES SOC during discharge period (7th August 2013)

The discharge peak-shaving algorithm is disengaged when SOC reaches 20%. As the online SOC estimator from the Hemsby trial EES system dynamically gives a pessimistic estimation of the SOC during discharging, the peak-shaving algorithm disengages in the field trials due to low SOC. Studies have shown that SOC estimates from the trial in steady-state conditions are consistent with what is predicted by the model. In contrast the peak-shaving algorithm in the EES system model is disengaged by low SOC but the reduction in the powerflow below the threshold value. This shows that SOC estimation algorithms can have a large impact on the capability of EES systems in distribution networks. In this case it reduced the available energy capacity of the EES system for peak-shaving by 16.5%.

7. Post-trial analysis – Extension, Enhancement, Extrapolation and Generalisation

7.1. Case study network

As stated earlier in section 4, and illustrated in Figure 4, the impact of the EES is relatively small on the local distribution network. To evaluate the Hemsby EES systems, another validated case study network, where an identical system to that installed at Hemsby could make a relatively significant impact on powerflow on an element of infrastructure, was selected. This allowed investigation of the capability of systems similar to the Hemsby EES system to manage powerflows in realistic future scenarios

where there is a large penetration of LCT based load and generation (heat pumps and PV) resulting in powerflows exceeding the designed thermal limits of an element of infrastructure.

The network is representative of a rural network in the UK, and is part of the infrastructure owned and operated by Northern Powergrid in the North East of England. A detailed MV and LV network model has been built and validated by MV and LV measurements from the CLNR smart grid project [6, 19]. 189 domestic customers are connected downstream of this substation on the LV feeders. An EES system identical to Hemsby in terms of power and energy is installed on the LV side (0.4kV) of the MV/LV (20/0.4kV) transformer of this case study network, as illustrated in Figure 8.

Figure 8: Single line diagram of case study rural network

7.2. Extension

The extension phase requires trials to be extended in terms of time or simulate trials that could not be carried out. As a different case study network has been selected for further analysis, extending the Hemsby EES trials would not contribute to the objective of this evaluation.

7.3. *Extrapolation*

In order to provide a baseline assessment of the capability of this network to accommodate heat pumps or PV generation installations, heat pump and PV are increased in the case study LV network until the load or generation at peak, on the MV/LV transformer, is equal to the designed thermal rating. This approach gives a more sophisticated assessment which accounts for the energy capacity of the EES system and load profiles at this substation based on future scenarios.

In the following sections, generic load and generation profiles for heat pumps and PV domestic installations are presented. These are derived from field trials of air source heat pump (ASHP) and PV installations throughout the UK using over a year's data as part of CLNR [6, 19]. The model of the EES system is identical to the model validated in section 6.3 except for the additional functions detailed in section 4. The principal components of the EES system model remain in this analysis and therefore these models retain their validity. It should be noted in this analysis that the downstream LV network is adequate to ensure that the voltage remains within statutory limits even at high penetrations of ASHP and PV assuming a uniform distribution across the LV network.

7.3.1. *Winter peak and summer minimum models for case study network*

Using the detailed secondary substation level data available from CLNR, from February 2013 to March 2014, it was possible to evaluate what the existing kVA capability is at this substation for the connection of further load. From analysis of this dataset, it was found that winter peak occurs on the 21st January 2014 and summer minimum occurs on the 10th July 2013. Figure 9 illustrates the real and reactive power profiles experienced by the case study transformer during the summer minimum 2013 and winter peak 2013/2014.

Figure 9: Case study MV/LV transformer real and reactive profiles for summer minimum 2013 and winter peak 2013/2014

7.3.2. ASHP model development

An ASHP load model suitable for this analysis is derived from data from the CLNR project programme [6, 65]. 277 households with operational ASHPs units have been equipped with disaggregated monitoring equipment that monitors household load and ASHP load at a 1-minute time resolution. Analysis of this current dataset established that the 17th Jan 2013 represented the worst case scenario in terms of loading for the ASHP units. Analysis of weather data indicates that this coincided with a cold spell across the UK [66]. In order to develop a model of a future worst case scenario the 95th percentile profile, as illustrated in Figure 10, is used.

Figure 10: Generic GB winter peak ASHP installation daily load profile (95th percentile) [6]

7.3.3. PV model development

A PV generation model suitable for this analysis is also derived from data from the CLNR project programme [6, 65]. 161 households with PV installations have been equipped with disaggregated monitoring equipment that measures household load and PV generation at a 1-minute time resolution. Analysis of this current dataset established that July 2013 was the month with the greatest peak daily PV generation across the installations. In order to develop a model of a future worst case scenario, the 95th percentile profile, as illustrated in Figure 11, is used.

Figure 11: Generic GB summer minimum PV installation daily generation profile (95th percentile) for July 2013 [6]

7.3.4. ASHP clustering on case study LV network

The active and reactive transformer load profiles for winter peak are used in combination with the generic ASHP load model to construct robust models of the powerflows through the transformer with increasing quantities of ASHP during winter peak. Figure 12 illustrates the transformer powerflow profile in a scenario where there are 65 ASHP installations (35% penetration) in the downstream LV network during the winter peak. It can be seen that the peak load of this profile approaches the designed thermal limit of the case study MV/LV transformer. Therefore, the installation of further ASHPs downstream of this transformer would require reinforcement of the network by replacing and uprating the MV/LV transformer.

Figure 12: Case study transformer powerflow profile with 65 ASHPs installed (35% penetration of ASHP) in LV network

The addition of the Hemsby EES system at the LV busbar of the case study transformer, running identical algorithms to those detailed earlier, enables the network to increase the number of ASHP installations to 95 (50% penetration) as illustrated in Figure 13. In this application of the peak-shaving algorithm, the threshold is fixed at the designed thermal limit of the case study transformer.

Figure 13: Case study transformer powerflow profile with 97 ASHPs installed (52% ASHP penetration) in LV network with Hemsby EES system

It can be seen from Figure 12 and Figure 13 that the EES system exits from peak-shaving operation as the powerflow drops below the thermal limit rather than due to low SOC. However, this was found to be the largest number of ASHP units that could be installed whilst maintaining consistency with the design and operation of the peak-shaving algorithm deployed in the field trial EES system.

Figure 14: Case study EES parameters with 97 ASHPs installed (52% ASHP penetration) in LV network with Hemsby EES system

7.3.5. PV clustering on case study LV network

The active and reactive transformer powerflow profiles for summer minimum have been used in combination with the generic PV generation model to construct robust models of the powerflows through the transformer with increasing quantities of PV during summer minimum. Figure 15 illustrates the transformer powerflow profile in a scenario where there are 113 PV installations (61% penetration) in the downstream LV network during the summer minimum. It can be seen during peak PV generation the powerflows approach the designed thermal limit of the case study MV/LV transformer. Therefore, the installation of further PV installations downstream of this transformer would replacement and uprating of the MV/LV transformer.

Figure 15: Case study transformer load with 113 PV installations (61% penetration)

The addition of the Hemsby EES system at the LV busbar of the case study transformer, running the identical algorithms to those detailed in the results and validation phase, enables the network to increase the number of PV installations to 132 (71% penetration) as illustrated in Figure 16. In this application of the peak-shaving algorithm, the threshold is fixed at the thermal limit of the case study transformer, as per the ASHP study.

Figure 16: Case study transformer loading 132 PV installations (71% penetration) in LV network with Hemsby EES system

It can be seen from Figure 16 and Figure 17 that the EES system exits from peak-shaving operation as the powerflow drops below the thermal limit rather than due to low SOC. As previously, this was found to be the largest number of PV units that could be installed whilst maintaining consistency with the design and operation of the peak-shaving algorithm deployed in the field trial.

Figure 17: Case study EES parameters with 70% PV penetration in LV network with Hemsby EES system

Under the maximum PV cluster network export scenario the maximum EES import is 60kW and uses 120kWh out of a total energy capacity of 200kWh to enable connection of the PV units. In the peak ASHP scenario the maximum EES export is 58kW and uses 108kWh out of a total energy capacity of 200kWh to enable connection of the ASHP units. Modification of the algorithm for this application from what is deployed at Hemsby could use more of the power and energy capability of the EES system however such modifications have practical implications e.g. the lifetime of the EES system, as they would require deeper charge/discharge cycles.

7.4. Enhancement

Additional studies were undertaken to complete the enhancement phase of the methodology. In these studies, similar EES systems to the Hemsby system with different power ratings and energy capacities were investigated using varying penetrations of PV and ASHPs to determine what power rating and energy capacity an EES system would need in these scenarios. In addition, the effect of battery degradation is also considered in this study. The usable capacity of a network-supporting EES has been estimated to decrease by 1.2 – 1.5% per year [50]. In this study a battery is deemed to have reached End of Life (EOL) if the energy capacity is 80% of its original energy capacity [67]. The results of these studies are presented in Table 1. Reference source not found..

417 **Table 1: Additional ASHP/PV connection capability at case study secondary substation**

	ASHP		PV	
	EES max power (kW), $\Delta Installations/(\Delta Penetration)$		EES max power (kW), $\Delta Installations/(\Delta Penetration)$	
Baseline	N/A	65 / (35%)	N/A	113 / (60%)
+EES (100kVA/200kWh) - New	61.15	31 / (16.5%)	61.81	19 / (10.1%)
- EOL	56.26	28 / (15.2%)	53.94	17 / (9.2%)
+EES (200kVA/400kWh) - New	79.76	40 / (21.5%)	95.67	30 / (15.7%)
- EOL	74.32	37 / (20.1%)	82.97	26 / (14%)
+EES (300kVA/600kWh) - New	89.38	46 / (24.5%)	126.21	39 / (20.8%)
- EOL	84.10	42 / (22.6%)	108.37	34 / (18.2%)

418

419 It can be seen that battery energy capacity degradation reduces the capability of the EES to increase LCT penetration by
 420 approximately 10% in all cases. As larger numbers of ASHP or PV installations are connected, the power rating per customer
 421 remains relatively constant. In the case of the ASHP and PV clusters this is approximately equal the peak power
 422 consumption/generation of the generic ASHP and PV generic installation models. However the energy capacity of the EES
 423 system required per customer increases. These relationships for the ASHP and PV case study cluster networks are illustrated in
 424 Figure 18.

425

Figure 18: EES energy capacity/customer and additional penetration of LCT (Δ Penetration)

The differences between the ASHP and PV energy capacity/customer traces are due to the powerflow profiles resulting from the high ASHP and PV penetration scenarios. The ASHP cluster powerflow profiles result in relatively high MV/LV transformer capacity factors which indicates that the existing infrastructure is already being well utilised [12]. In contrast, the PV cluster profiles have much lower MV/LV transformer capacity factors due to PV generation has a relatively low capacity factor, in this case 0.302, in contrast to the capacity factor of the ASHP installations which is 0.777.

7.5. Generalisation

As the future load/generation profiles for the clustered networks are derived from representative and generic load and generation models, it can be shown that increasing penetrations of LCT will have a similar impact on the import and export profiles of other transformers with proportionally similar distributions of customers. Thus, similar relationships between energy storage rating and energy capacity with increasing LCT penetration, as shown in Figure 18, can be established.

7.6. Application of Methodology for assessment of other Network Services

This methodology could equally be applied to voltage control, system restoration or other network services. For example, if an assessment of the capability of energy storage to control voltage in order to reduce wind based generation curtailment was required an appropriately designed trial could include the trial of an energy storage unit in an area of network where wind generation is already connected but not causing any voltage problems. This would enable the validation of the energy storage and control model. The extension phase of the methodology would include the extension of the trial in simulation for a number of years using real or synthesised data. The extrapolation phase of the study would evaluate the impact of increasing penetrations of LCTs on the network on the operation of the network. Different locations and capacities of energy storage would be assessed in the enhancement phase of the methodology. Finally, a generalisation phase of analysis would be undertaken in which generic or representative networks, generic network loading and generation conditions and the validated energy storage and voltage control system models could be used draw broader conclusions about the operation of the systems in future distribution networks.

8. Conclusion

An EES system has been installed by UKPN at Hemsby in Norfolk, England in collaboration with ABB and university partners in the north-east of England. The project has practically demonstrated the capability of an EES system to contribute to local distribution network operation through peak-shaving, voltage control and levelling out of power fluctuations from the adjacent windfarm.

To enable this evaluation of this capability a trial design was developed which has informed the development of a subsequent trial design methodology used in CLNR [6, 7]. An adaptive peak shaving algorithm was developed to maximise the operation time of the EES system and the quantity of useful data that can be collected during the trial period. Future EES trials could provide more representative results by sizing the EES unit so that it has larger impact on the network.

A formalised trial analysis methodology, which has been developed as part of CLNR, of smart grid network intervention trials and includes methods to integrate data from literature and customer trials, is detailed. This methodology enables development of robust models of networks, smart grid network and LCTs that are used collaboratively to evaluate future scenarios where networks are near their thermal or voltage limits due to large penetrations of LCT load and generation.

The methodology enables use of detailed, validated models of electrical networks and smart grid network intervention and enables integration of LCT profiles unlike previous approaches. However, the methodology currently doesn't integrate an economic analysis of whole lifecycle costs of the deployment of EES to provide a network service, which has been the focus of other research.

The peak-shaving trials of the Hemsby EES system are presented as an illustrative example of an application of this methodology. It was found that communications latency and measurement errors can impact on the peak-shaving capability of an EES system in practice. In particular, the dynamic error in the SOC estimation algorithm restricted the practical available energy capacity of the EES in the trial by 16.5%. The analysis of the trial data, enabled development of validated models of the Hemsby EES system.

A representative case study network from the CLNR program, where the Hemsby EES system could have more significant impact on local powerflows, was described. This network model was validated using the measurements from LV monitoring systems deployed with customers across GB as part of this project programme. Generic models of ASHP and PV installations, based on data from the GB wide trials of ASHPs and PV installations from the CLNR project programme were presented. Models of the powerflow for case study ASHP and PV cluster were synthesised using a combination of these models which enabled evaluation of the capability of this EES system to enable connection of clusters of these LCTs on this network.

A sensitivity analysis was performed on similar EES systems with smaller and larger power ratings and energy capacities which also considered battery degradation. It was found that the relationship between the energy capacity required of the EES and the number of additional ASHP or PV installations was non-linear particularly as the MV/LV transformer capacity factor approaches unity. The implication of this for the ASHP cluster network is that as the ASHP penetration increased beyond 15% the rate of increase of energy storage capacity required increases rapidly. It should be noted that the use of energy storage for

peak shaving has the effect of increasing the load factor and increasing the utilisation of the MV/LV transformer. More generally, the forecast MV/LV transformer capacity factor during maximum real power import/export conditions has a large impact on the final cost of an EES system for peak shaving system.

The studies indicated that battery energy capacity degradation to 80% of original capacity, which was defined to be end of usable life, reduces the capability of the EES to increase LCT penetration by approximately 10%. Therefore, in a practical implementation the EES unit should be sized to allow for this degradation in performance. The rate of degradation of an EES unit is a function of the operating regime of the unit which is itself a function of the network and market services that the individual EES unit is providing.

490 **Appendix A – Hemsby EES Control Algorithm**

491
492 **Figure A.1: EES control algorithm**

493 **References**

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