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Potential value of energy storage in the UK electricity system — Source link

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Published on: 01 Sep 2015

Topics: Energy accounting, Energy storage, Energy conservation, Efficient energy use and Energy engineering

Abstract (200 words)

This paper assesses the value of distributed energy storage (ES) and informs the business case for its multiple applications in the future Great Britain (GB) electricity system. In contrast to earlier studies that focus on the benefits of ES for system operation and development, this work analyses the value that ES may deliver to the owner. For this purpose, three models are proposed and applied to analyse the benefit of ES with applications in energy and ancillary service markets, revenue maximisation in the context of Feed-in-Tariff (FiT) and carbon footprint minimization. A large set of studies are carried out to quantify the commercial and carbon benefits of ES for those applications. Sensitivity analysis across various scenarios is performed to understand the key drivers for the value of ES and how it is affected by ES parameters and other factors such as network constraints, prices of energy and ancillary services, and inherent energy system characteristics. A review of current and near-term storage technology costs and functionality is also presented.

Keywords:

Renewable energy; Electrical engineering & distribution; planning and scheduling

List of notation

$N_s(n)$	Charge/discharge state (1/0) of storage unit s at node n
$E_s(n)$	Stored energy of storage unit s at node n [MWh]
$P_s^c/P_s^d(n)$	Charge/discharge power rate of storage unit s at node n [MW/h]
$P_s^{Res}(n)$	Scheduled response regulation of storage unit s at node n [MW]
$P_s^{STO}(n)$	Scheduled STOR service of storage unit s at node n [MW]
E_s^{min}/E_s^{max}	Minimum/maximum stored energy of storage unit s [MWh]
P_s^{cmin}/P_s^{cmax}	Minimum/maximum charge power rate of storage unit s [MW]
P_s^{dmin}/P_s^{dmax}	Minimum/maximum discharge power rate of storage unit s [MW]
P_s^{ResMAX}	Maximum response capability of storage unit s [MW]
P_s^{STOMAX}	Maximum STOR service capability of storage unit s [MW]
P_{DN}^{Max}	Maximum capacity of distribution network DN [MW]
η_s^c/η_s^d	Charge/discharge efficiency of storage unit s

ρ_s	Loss rate of storage unit s
$a(n)$	Parent node of n
$D(n)$	Local demand level at node n [MWh]
$Pr_{RT}(n)$	Real time price at node n [£/MWh]
$Pr_{Res}/Pr_{STOR}(n)$	Frequency response/ STOR service price at node n [£/MW/h]
$\pi(n)$	Probability at node n
Pr_{GEN}	Generation tariff [£/MWh]
Pr_{Retail}/Pr_{EXP}	Retail/exporting electricity price [£/MWh]
$P_{grid}(t)$	Power injection from grid at hour t [MW]
$P_{PV}^{Gen}/P_{PV}^{EXP}(t)$	Power generation/exported of distributed generation at hour t [MW]
$P_s^c/P_s^d(t)$	Charge/discharge rate of storage unit s at hour t [MW]
$E_{co2}(t)$	Average grid emission rate at hour t [g/kWh]

1. Introduction

In recent years, concerns over climate change have increased the demand for renewable energy sources (RES) and other low carbon generation technologies such as nuclear plants. With respect to balancing capabilities, these technologies are less flexible than traditional fossil fuel plants. Therefore, the increased balancing requirements due to high RES penetration have to be provided by other sources. In this context, energy storage (ES) will potentially play an important role in supporting the integration of RES.

Extensive studies have been conducted to understand the value of ES. Previous work evaluated its capability to perform energy arbitrage (Energy Research Partnership, 2011) and provide ancillary services (Black & Strbac, 2007). Multiple-service provision from ES was investigated in (Strbac, et al., 2012) (stoRE, 2013). Stochastic scheduling is particularly suitable for analysing ES in a system with high RES penetration (Tuohy & O'Malley, 2011), since the capacity of ES could be optimally split between energy arbitrage and ancillary service provision under various system conditions.

The above studies provide insights into the overall benefits of ES to the system, while other studies assess the techno-economic performance from the investor's point of view. Authors in (Sioshansi, et al., 2009) estimate the profit of ES in PJM, but by arbitrage-only. The profit of ES with combined services provision was studied in CAISO by (Byrne & Silva-Monroy, 2012). Those studies use historical market prices and normally assume perfect information of these prices. However, in the future system with high RES penetration, electricity prices would become more volatile and uncertain.

In addition to direct participation in the wholesale market, ES can be used for other applications. The analysis in (Pudjianto, et al., 2014) shows the benefits of ES in supporting the distribution network; while ES is applied to increase the revenue for non-firm wind generation in (Gill, et al., 2013).

This paper focuses on an assessment of the value that distributed ES may deliver to the owner in various applications. The structure of the paper is summarised as:

1. Value of ES in energy and ancillary services markets (Section 2)
2. Site-specific value of ES (Section 3)
3. Value of ES applied to maximise FiT revenue (Section 4)
4. Value of ES applied to reduce carbon footprint (Section 5)

For this purpose, three optimization models are proposed and implemented in this paper:

1. Stochastic system and storage scheduling model (Section 2 and Section 3)
2. Revenue maximisation model in the context of FiT (Section 4)
3. Carbon footprint minimization model (Section 5)

Sensitivity analysis across various scenarios has been carried out to analyse the key drivers for the value of ES and how it is affected by ES parameters and other factors such as prices of energy and ancillary services, network constraints and inherent energy system characteristics. The assessment in Chapter 2 - Chapter 5 is carried out with the technology-agnostic approach. The storage is only represented through a limited number of generic key characteristics, such as power rating of storage (charging and discharging), round trip efficiency, and energy storage capacity. This allows a wide range of technologies to be mapped onto the results. Then Chapter 6 provides a review of the costs and performance of some particular storage technologies. Based on the results of Chapter 2-6, the potential storage technologies are identified in Chapter 7.

2. Assessment of the value of ES in the energy and ancillary services markets

A set of studies have been carried out to investigate the applications of ES for multiple commercial activities in energy and ancillary services (balancing, short-term operating reserve (STOR) and frequency response (FR)) markets. The objective of these studies is to investigate the changes in the value of ES driven by changes in the generation mix and the corresponding energy and ancillary service prices. Therefore, the value of ES is assessed for the present system, as well as two future low-carbon systems (2030) with different levels of flexibility (as shown in Table 1):

1. Present System: the system is dominated by fossil fuel plants. The analysis is performed using historical price data from the spot market in 2012 (Elexon, n.d.).
2. Future inflexible system: the system is characterized by high penetration of RES and base-load plants, as well as low capacity of Open Cycle Gas Turbines (OCGTs).
3. Future flexible system: this system contains the same level of RES as the inflexible system but with lower capacity of base-load plants and higher capacity of OCGTs.

Table 1 Generation mix in the present and future system

(GW/%)	*Base load*	*Coal*	*CCGT*	*OCGT*	*Storage*	*Wind*
Present System	15.3(19%)	22.8(29%)	27.2(35%)	4(4%)	2.7(4%)	6.9(9%)
Future Flexible System	20(19%)	0(0%)	30(29%)	20(19%)	2.7(3%)	30(30%)
Future Inflexible System	30(29%)	0(0%)	37(36%)	3(3%)	2.7(3%)	30(30%)

Table 2 shows the technical, economic and emission characteristics of generation technologies. The operating cost of generators is divided into: variable, no-load, and start-up costs. The fuel and carbon prices are obtained from (IEA, 2013). RES is assumed to submit negative bid prices for a curtailment (equal to a Renewables Obligation Certificates (ROCs) value of 50 £/MWh). The capacity of CCGT/OCGT is equally allocated among three categories with different variable costs.

Table 2 Characteristics of generators in the future system

	P^{max}/P^{min} (MW)	*No-load Cost* *(£/h)*	*Variable Cost* *(£/MWh)*	*Start-up Cost* (£/start-up)	*Start-up Time* (hrs)	*Response* (MW)	*Min up/down time* (hrs)	*Emission* *(kg/MWh)*
Base	500/500	303	7.1	N/A	N/A	0	N/A	0
CCGT	500/250	8357	70/85/100	20500	4	100	4	394
OCGT	140/56	4200	250/350/450	0	1	70	1	557

2.1 Assessment framework

The study is carried out in 2 stages (Figure 1). The first stage is to derive the electricity prices using the stochastic system scheduling model. In the second stage, the stochastic storage scheduling model determines the operation of ES to maximize the expected profit based on the price information from the system scheduling model. During the second stage, the capacity of ES under investigation is assumed to be small enough that can be modelled as a price taker (Sioshansi, et al., 2009).

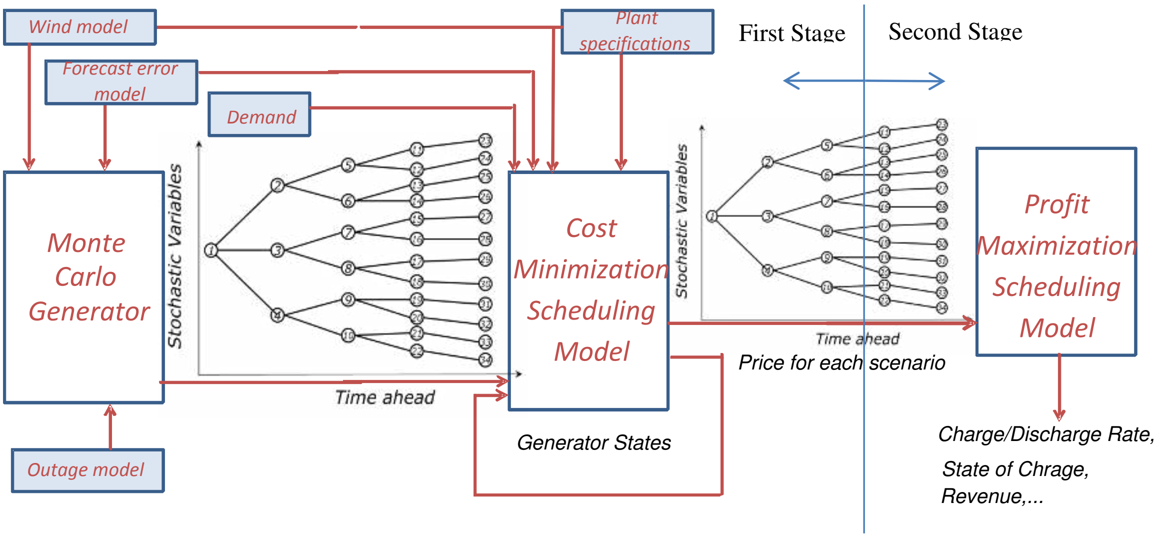


Figure 1 Assessment framework to evaluate distributed ES

2.1.1 Stochastic generation scheduling model and settlement scheme

The stochastic generation scheduling model (Sturt & Strbac, 2012) minimises the expected operating cost across all the possible realisations of uncertain variables including wind production, demand and conventional generation availability. The full range of possible realisations is firstly discretised into a set of representatives by user-defined quantiles, and then the corresponding probabilities $\pi(n)$ can be calculated by using the trapezium rule. These representatives and the associated probabilities are used to build a scenario tree. The optimization is subject to dynamic constraints for thermal and bulk storage units. Operating reserve requirements are endogenously optimised within the model. The scheduling is performed on a rolling basis, in which only here-and-now decisions are fixed and all subsequent decisions are discarded.

Alternative settlement schemes have been proposed for the stochastic system scheduling (Wong & Fuller, 2007). The energy-only real-time pricing scheme is adopted in this paper, which has been implemented by (Karangelos & Bouffard, 2012) to investigate the value of demand side flexibility. Under this scheme, all the compensation is based on the actual state of the system. After the commitment decisions are made, the model calculates the optimal dual variables in each node of the scenario tree. In order to provide a predition for the real-time price, it is necessary to remove the probabilities from these optimal dual variables: if $p(n)$ is the optimal dual variable for node n and $\pi(n)$ is the probability of reaching node n, the forecasted price for node n can be calculated as $p(n)/\pi(n)$. A similar scenario tree can be built, containing the forecasted real-time prices and the associated probabilities for each node. For the arbitrage only case, the price is calculated in a single scenario which describes the most-likely value of stochastic variables in day-ahead. This assumption corresponds to the day-ahead energy only market. In addition, FR and STOR services are assumed to be contracted ahead of operation scheduling on an annual or monthly basis.

2.1.2 Profit maximization scheduling model of ES under price uncertainty

The storage scheduling model optimizes the operation of ES to maximise its expected profit based on the price scenario tree. The scheduling is also performed using rolling planning. After all the uncertainties are realized, the final prices in each timestep are obtained and used to settle the market.

The objective is to maximize the expected profit:

$$\sum_{n\in N}(\pi(n)\big(Pr_{RT}(n)\big(P_s^d(n)-P_s^c(n)\big)+Pr_{Res}(n)*P_s^{Response}(n)+Pr_{STOR}(n)*P_s^{STOR}(n)\big)\big) \tag{1}$$

subject to storage physical constraints include: (i) charge rate limits (Equation 2) and discharge rate limits (Equation 3); (ii) stored energy balance constraints (Equation 4); (iii) constraints associated with the amount of energy that can be stored (Equation 5).

$$N_s(n)P_s^{cmin} \leq P_s^c(n) \leq N_s(n)P_s^{cmax} \tag{2}$$

$$(1-N_s(n))P_s^{dmin} \leq P_s^d(n) \leq (1-N_s(n))P_s^{dmax} \tag{3}$$

$$E_s(n) = \rho_s E_s(a(n)) + \left(\eta_s^c P_s^c(n) - \frac{P_s^d(n)}{\eta_s^d}\right) \tag{4}$$

$$E_s^{min} \leq E_s(n) \leq E_s^{max} \tag{5}$$

Provision of FR and STOR requires ES to provide extra power for 30 minutes and 2 hours respectively. Therefore, additional constraints are developed for ES to keep enough headroom and stored energy, if contracted to provide these services.

Ancillary service provision constraints include: (i) maximum FR capability (Equation 6) and STOR service capability (Equation 7); (ii) storage headroom constraints associated with response provision (Equation 8) and STOR provision (Equation 9); (iii) stored energy constraints associated with response provision (Equation 10) and STOR provision (Equation 11).

$$0 \leq P_s^{Response}(n) \leq P_s^{ResponseMax} \tag{6}$$

$$0 \leq P_s^{STOR}(n) \leq P_s^{STORMax} \tag{7}$$

$$P_s^{Response}(n) \leq \left((1 - N_s(n))P_s^{dmax} - P_s^d(n) + P_s^c(n)\right) \tag{8}$$

$$P_s^{STOR}(n) \leq P_s^{dmax} - P_s^d(n) + P_s^c(n) - P_s^{Response}(n) \tag{9}$$

$$0.5 * P_s^{Response}(n) \leq E_s(n) - E_s^{min} \tag{10}$$

$$2 * P_s^{STOR}(n) \leq E_s(n) - E_s^{min} - 0.5 * P_s^{Response}(n) \tag{11}$$

The optimization is solved by using a mixed integer linear programming solver developed by FICO (FICO, n.d.), which is linked to a C++ simulation application via the BCL interface.

2.2 Value of distributed ES in the energy and ancillary services market

The above assessment framework is applied to investigate the applications of ES for multiple commercial activities in energy and ancillary service markets. Unless otherwise specified, the following studies assume that the energy capacity of ES is large enough for discharging at maximum output for 4 h and the round-trip efficiency is 75%.

2.2.1 Impact of increased RES and generation inflexibility

In this section, the value of ES is analysed in the proposed scenarios. For future systems, two cases are studied:

(1) ES performs arbitrage-only in the day-ahead energy market: the scheduling of ES is made and fixed in the day-ahead market, based on the prices calculated by the most-likely forecast of uncertain variables.

(2) ES participates in both the day-ahead energy market and the real-time balancing market: the scheduling of ES is made based on the real-time price scenario tree, and updated on a rolling basis.

The value of ES is calculated by dividing the revenue of ES over its lifetime with the energy capacity (kWh). As shown in Figure 2, the value is between £100 (current) - £650 (future) per kWh, which is higher in future systems because of the increasing volatility in real-time prices caused by the high RES penetration. The value of ES in the present system is in line with the results presented in (Sioshansi, et al., 2009). Moreover, by providing balancing services, the additional value obtained by ES is significant. Due to the difficulty of system balancing (high real-time price) and high RES curtailment (negative real-time price), the price volatility in the inflexible system is higher and therefore the corresponding value of ES is also higher.

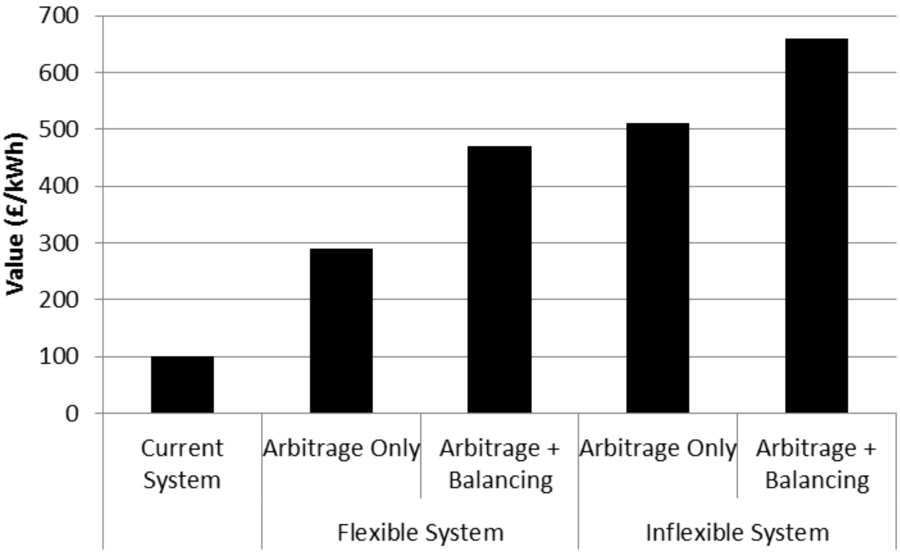


Figure 2 Value of ES across different systems

2.2.2 Impact of energy capacity and efficiency on the value of ES

Studies are conducted to understand the dependency of the value of ES on the energy capacity and the round-trip efficiency. The result is expressed as a ratio between the value with a specified energy capacity/efficiency and the value of ES in the base case.

Figure 3 shows that the value (£/kWh) drops when the energy capacity is higher. This suggests that the demand to keep the energy in ES for a long period is relatively low. Clearly, this is likely to be system-specific; as in some systems, it may be required to have a large energy reservoir.

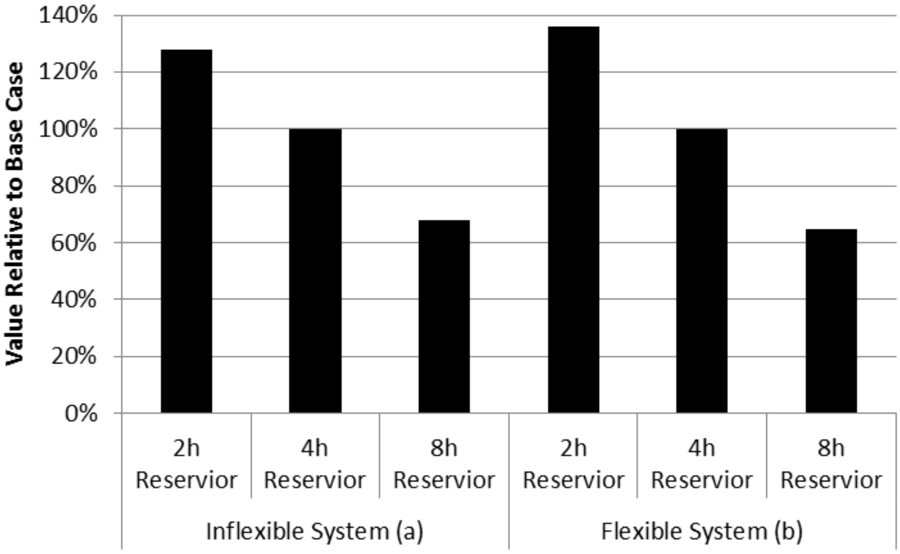


Figure 3 Impact of energy capacity on the value of ES

For the impact of the round-trip efficiency, as discussed by (Gill, et al., 2013), negative prices may provide incentives to increase losses. Hence, ES with lower energy efficiency could obtain a higher value. This case is illustrated in the inflexible system (Figure 4 (a)). In the flexible system (Figure 4 (b)), curtailment of RES is less and therefore negative prices occur less often. The improved efficiency increases the value but only marginally.

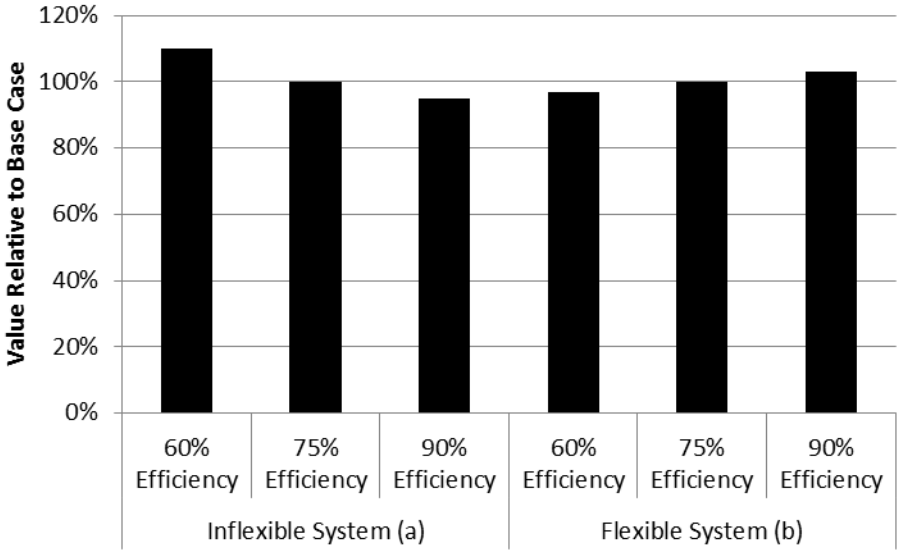


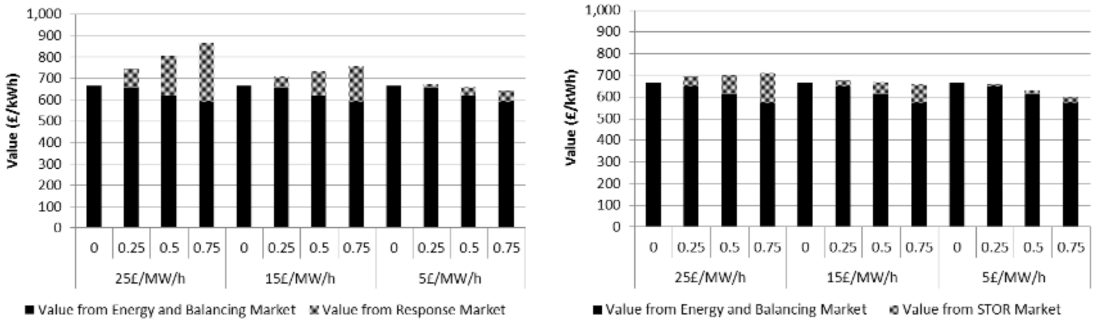
Figure 4 Impact of round-trip efficiency on the value of ES

2.2.3 Value of ES by providing multiple ancillary services

In order to maximise the revenue, ES can also provide additional commercial services including FR and STOR. For specific time windows (between 7 and 9 am and between 5 and 9 pm are chosen in this paper), part of ES's capacity are dedicated to providing these services. A certain amount of stored energy is also required to ensure the deliverability. The studies analyse the value of ES in the future inflexible system by using a range of market prices for FR (10 - 50 £/MW/h) and for STOR (5 - 25 £/MW/h), as well as various percentage (0-75%) of storage capacity allocated for these services.

The results in Figure 5 (a) indicate that by providing the extra FR service, the value of ES can be enhanced, especially if the market price is attractive (e.g. £50/MW/h). Due to the additional operation constraints, the value obtained from energy and balancing market decreases, but not significantly since the service is provided only for few hours a day.

For the STOR service (Figure 5 (b)), the ability of ES to offer this service can also improve its value, although this depends on the market prices. Reduction in the revenue from energy and balancing activities caused by STOR provision is higher than that by FR provision because of a longer service provision requirement. The results in Figure 5 (b) also demonstrate that for some market prices, there exists an optimal capacity to provide STOR service (e.g. 25% in the 15 £/MW/h case).



(a) Frequency Response (b) STOR Service

Figure 5 Value of ES from real-time market and ancillary service market

3. Assessment of the site-specific value of ES

This set of studies quantifies the value of distributed ES installed at specific sites without the reinforcement of the local network. Therefore, ES may have to reduce its charge rate from optimal value during some hours with low price and high demand. As a consequence, ES may also lose some opportunities to discharge during some high price hours due to energy limits. The same model as in Section 2.1 is applied, but with the additional local network constraint:

$$D(n) + P_s^c(n) - P_s^d(n) \leq P_{DN}^{Max} \tag{12}$$

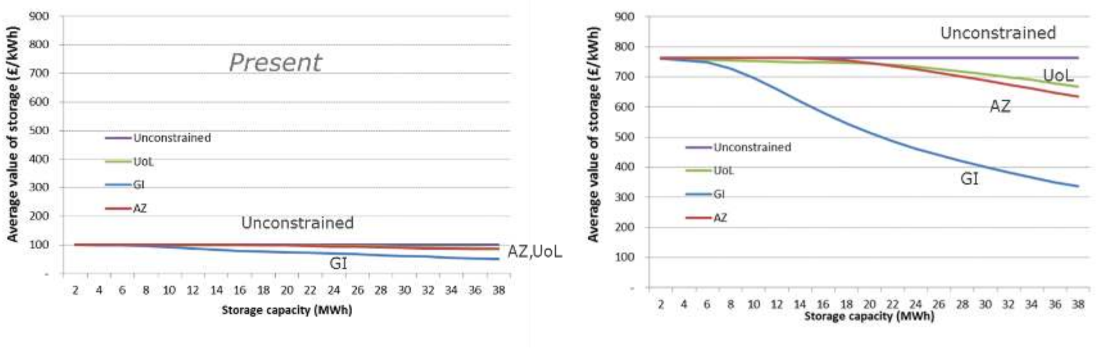
Three potential sites for ES applications are considered:

- A university (UoL) with a peak demand of 11MW
- An hospital (GI) with a peak demand of 4 MW
- A pharmaceutical company (AZ) with a peak demand of 8.8 MW

Due to the local network constraint, the operation of ES must be optimised taking into account the customer's load profiles at these specific sites. The profiles will depend on the nature of customer's activities and use of electricity. For example, the electricity load in a university during the evening and early morning is much lower compared to the load at day-time. While this is a general trend, the difference may be less significant for a hospital that runs 24 h. In this study, the load profiles were taken from the metered data.

The size of the various storage systems used in the following study is between 2MWh and 38MWh.The results in Figure 6 suggest that for a relatively small size ES, the value is not site-specific. In these cases, the network constraints are not binding and do not affect the storage operation. When the storage capacity increases up to a threshold, the effect of network constraints becomes visible. This threshold depends on the load profiles and the capacity of the local network. Among the three sites, GI has the lowest capacity then AZ and UoL. Thus, the threshold for GI is the lowest one, followed by AZ and then UoL. Figure 6 also suggests that, for the present system (a), the network capacity impact is relatively small as the price typically correlates well with the demand. However, in the future system (b) with a significant amount of

RES, the prices will be more volatile and the correlation between the demand and the prices will also be affected by the output of RES. Hence, the effect of the network constraint becomes much more significant. The optimal sizing of ES is a challenging task and a cost-benefit analysis is necessary to inform the optimal investment.



(a) Present system (b) Future system - Inflexible

Figure 6 Value of ES in different sites

4. Assessment of the value of ES applied to maximise FiT revenue

Since the introduction of FiT in 2010, the installed capacity of distributed generation (DG) has increased significantly in GB, particularly PV from 100 MW to more than 2 GW in 2013. The FiT rewards not only the energy produced by DG but also the ability to self-consume the output. Because of the significant difference between the retail price and the export tariff, the application of ES to maximise the FiT revenue of DG is attractive. In order to assess this value, a year-round ES optimisation is performed to maximise the FiT revenue. The benefit of ES comes from improving self-consumption of PV production and consequently reducing the PV output exported back to the grid.

The objective is to minimize the total payment:

$$\sum_{t\in T}\left(Pr_{Retail} * P_{grid}(t) - Pr_{GEN} * P_{PV}^{GEN}(t) - Pr_{EXP} * P_{PV}^{EXP}(t)\right) \tag{13}$$

subject to local load balance constraints:

$$D(t) = P_{Retail}(t) + P_{PV}^{Gen}(t) - P_{PV}^{EXP}(t) - P_{s}^{c}(t) + P_{s}^{d}(t) \tag{14}$$

The ES physical constraints remain the same as in (Equation 2) - (Equation 5).

A 30 kW PV system is assumed to be installed at a medium commercial building with the peak load of 25 kW, and the annual energy consumption of 140 MWh. The load factor of the PV system is 10% and therefore, the PV system contributes around 19% of the annual load. The generation tariff, export tariff and retail price are assumed to be 12.57p/kWh, 4.64p/kWh and 15p/kWh respectively. The size of ES used in the following studies is between 4kWh to 76kWh. As shown in Figure 7, the annual export of PV energy decreases in line with the increased capacity of ES. With circa 50 kWh of storage, the export is no longer visible. With the improved self-consumption, the revenue from FiT increases in line with the increase in ES capacity until a certain point where there is no export to the grid.

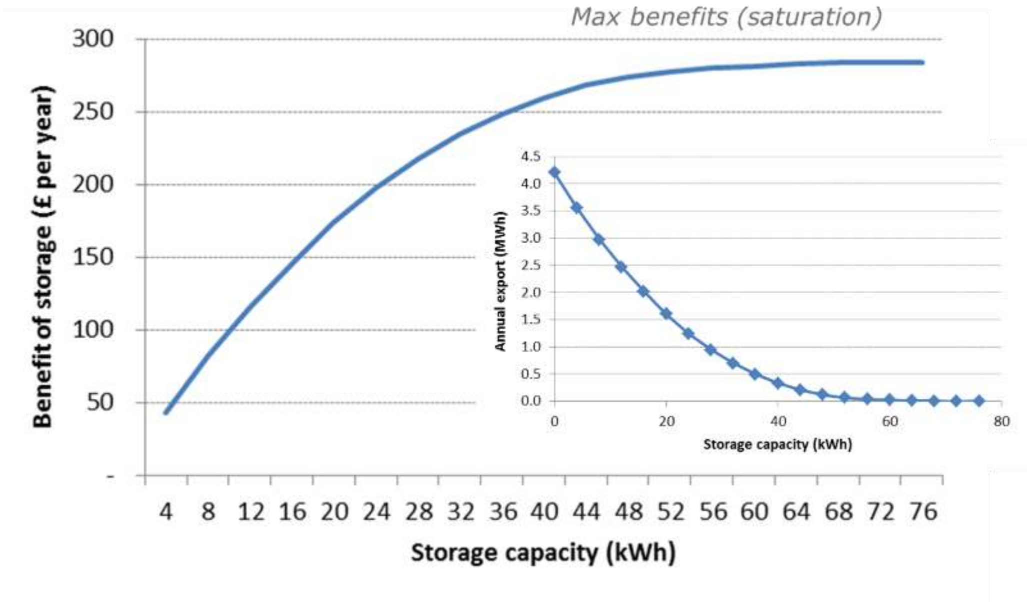


Figure 7 Increased self-consumption and benefit of ES

Since the value of ES in this application depends on the demand to reduce the PV output exported to the grid, the value certainly depends on the coincidence level between the local load and the PV output. In order to illustrate this, two different load profiles are compared. For Load(1) (base case), the peak demand occurs between 7am and 10am, and between 4pm and 9pm. Between 10am and 4pm, the demand is relatively low. Load(2) has flatter load profile with the peak load occurs between 10am and 9pm. While the PV produces between 9am and 7pm (Spring/Autumn profile). These profiles are shown in Figure 8 (right).

The value of ES for these two load profiles is depicted in Figure 8 (left). As the load profile of Load(2) coincides better with the PV output, the demand for ES to improve the self-consumption is less than that of Load (1). Consequently, the value of ES for Load(2) is much lower than that for Load (1). The results also suggest that in this application, ES will compete with active demand side management measures.

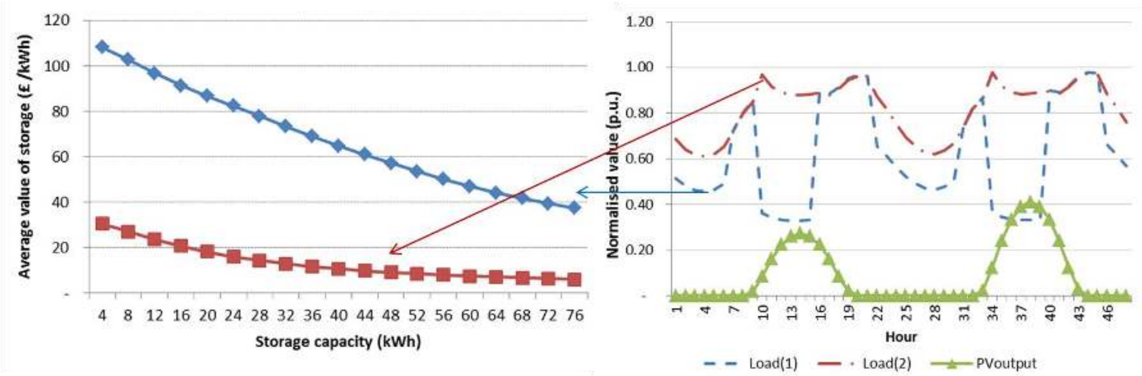


Figure 8 Impact of coincidence level between load and PV output on the value of ES

5. Assessment of the value of ES applied to reduce carbon footprint

As climate change awareness increases, incentives may increase to use ES to manage carbon footprint. Although this may not have direct economic benefits in terms of energy trading, it may generate indirect or social benefits, which in turn deliver some economic value.

The objective is to minimize the total carbon emission:

$$\sum_{t \in T} P_{grid}(t) * E_{co2}(t) \tag{15}$$

Subject to local load balance constraints:

$$D(t) = P(t) - P_s^c(t) + P_s^d(t) \tag{16}$$

The ES physical constraints remain the same as in (Equation 2) - (Equation 5).

An application of ES in a commercial building is investigated (Figure 9 – left diagram). The customer's peak demand is 2 MW with a load factor of 64%. The annual carbon footprint of this customer is calculated based on the product of load and grid CO2 emissions in each hour. The grid CO_2 profile is derived from the system scheduling in stage 1. Without ES, the annual emissions are 696 ton/year and the average carbon footprint is 62 g/kWh. In this system, we investigate the benefit of 1-MW ES with 5 h of energy capacity. Due to the small size of ES, it is reasonable to assume that the changes in dispatch and grid CO2 emissions are negligible.

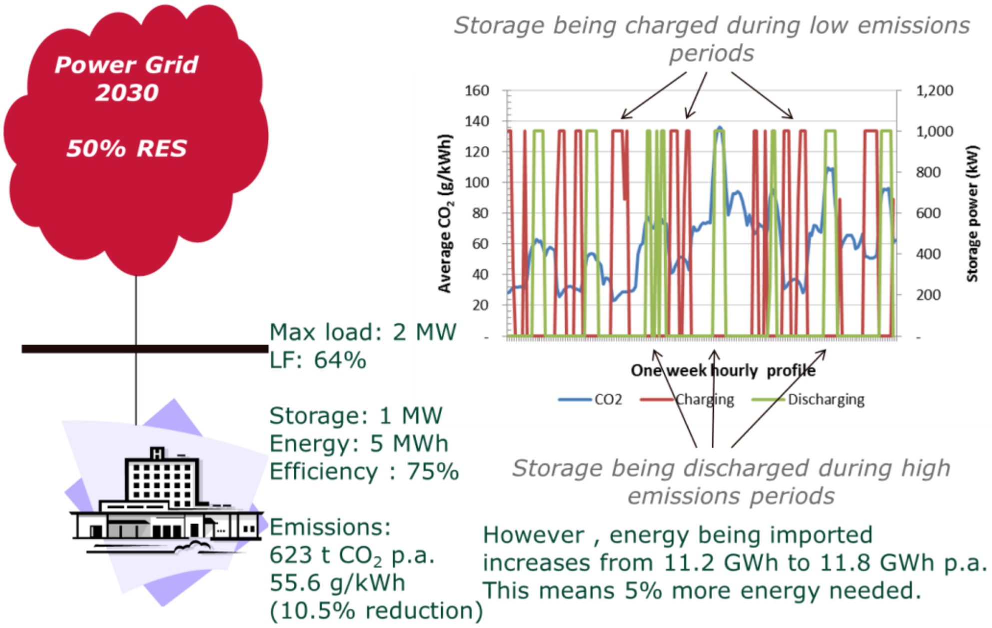


Figure 9 ES cycles following the grid CO_2 profiles for CO2 minimisation

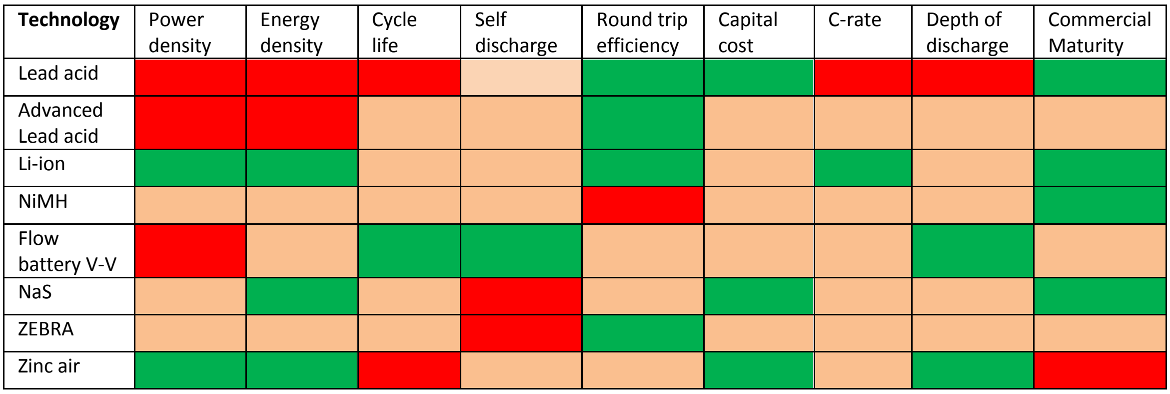
The results (Figure 9 – right diagram) show ES being charged during low-emission periods and discharged during high-emission periods. By using this operation strategy, the annual carbon footprint decreases from 696 ton/year to 623 ton/year, which constitutes 10.5% reduction in carbon footprint. This includes the impact of an increased annual energy consumption due to the efficiency losses of ES, as the energy imported from the grid increases from 11.2 GWh/year to 11.8 GWh/year.

6. Review of ES technologies

This section reviews the technologies best suited for grid-scale distributed ES from kW to MW in power and a few hours in energy capacity. The current status as well as projected performance and costs in 2020 are discussed. The DOE/EPRI Electricity storage handbook (Akhil, et al., 2013) provides an excellent overview of current ES technology status and costs, which has been used as the basis of the current cost data. This is further informed by the 2012 PNNL report (Kintner-Meyer, et al., 2012) along with data in (Ferreiraa, et al., 2013) and

(Chatzivasileiadi & Eleni Ampatzi, 2013), which provides some current cost and performance data and some projections up to 2020.

Figure 10 attempts to rank each of the technologies reviewed in terms of key characteristics, with red meaning that the technology is less suitable or has sigincifant disadvantages, green meaning that it is more suitable and/or has important advantages and amber meaning that it displays some of both.



Technology	Power density	Energy density	Cycle life	Self discharge	Round trip efficiency	Capital cost	C-rate	Depth of discharge	Commercial Maturity
Lead acid	🟥	🟥	🟥	🟧	🟩	🟩	🟥	🟥	🟩
Advanced Lead acid	🟥	🟥	🟧	🟧	🟩	🟧	🟧	🟧	🟧
Li-ion	🟩	🟩	🟧	🟧	🟩	🟧	🟩	🟧	🟩
NiMH	🟧	🟧	🟧	🟧	🟥	🟧	🟧	🟧	🟩
Flow battery V-V	🟥	🟧	🟩	🟩	🟧	🟧	🟧	🟩	🟧
NaS	🟧	🟩	🟧	🟥	🟧	🟩	🟧	🟧	🟩
ZEBRA	🟧	🟧	🟧	🟥	🟩	🟧	🟧	🟧	🟧
Zinc air	🟩	🟩	🟥	🟧	🟧	🟩	🟧	🟩	🟥

Figure 10 Characteristics of reviewed ES technologies.

Several technologies offer current ES costs of < 300 £/kWh, namely conventional lead acid (190 £/kWh), sodium sulphur (NaS) (230 £/kWh), and zinc air (120 £/kWh). However all have disadvantages, namely limited life, charge and discharge rate and the lack of deep discharge capability of conventional lead acid, the need to maintain the operating temperature of sodium sulphur which results in a high self-discharge and its availability only in the MW/MWh range, and the current lack of maturity of zinc air. NiMH appears to be an expensive option for distributed ES at around 610-1100 £/kWh. Therefore the technologies best suited today for highly distributed ES at the kW/kWh range appear to be the advanced lead acid batteries and lithium ion batteries, with Li-ion offering higher rates of charge/discharge. For applications into the 100's kW/kWh range, NaS, sodium-nickel chloride (ZEBRA) and flow batteries are all promising, with 1MW systems available at 230 £/kWh for NaS, 320 £/kWh for ZEBRA, and 460 £/kWh for vanadium flow batteries. Neither advanced lead acid nor lithium ion appears to compete effectively at the MW scale in terms of cost. Zinc air offers the prospects of costs down to 120 £/kWh at this power level, but requires scale up and improvement in charge/discharge rate and cycle life.

Costs of some technologies are expected to be reduced dramatically by 2020. Li-ion pack costs will be halved to 240 £/kWh driven by increasing volumes for electric vehicles (EVs). NaS and ZEBRA costs remain unchanged at 230 £/kWh and 300-600 £/kWh as there are only limited supplier, and there is no external driver for growth. Vanadium flow battery costs will be reduced to around 240 £/kWh, driven by significantly improved performance (currently being demonstrated in research labs). Advanced lead acid battery costs remain unchanged at around 420-840 £/kWh as there is no major external driver for volume, and the sector is already mature. NiMH costs remain unchanged or even increased as it is no longer developed for automotive applications. Zinc air remains a promising low cost option but still struggles to deliver a high cycle life.

7. Conclusion

This paper presents the analysis for distributed ES with multiple applications (including energy and ancillary services markets, FiT revenue maximization and carbon emission reduction). A large set of studies has been carried out to understand the value of ES and the key drivers that affect the value across different scenarios.

The results suggest that in the energy and ancillary services markets, the value of ES is mainly driven by the temporal arbitrage opportunities created by volatility in either or both day-ahead and real-time (balancing) energy prices. The value is between £100/kWh and £650/kWh, which is higher in the future system due to increased price volatility caused by high RES penetration. On top of energy and balancing services, ES can also provide additional ancillary services e.g. FR. If the market prices for those services are attractive, these can add up to £200/kWh to the basic value of ES. The value of ES is shown to be site-specific in case when distribution network is constrained. The effect of network constraints will become increasingly significant in the future system and ES will facilitate cost-effective integration of low-carbon generation and demand connected to the constrained distribution networks. For the FiT revenue maximisation application, the value of ES (£108/kWh - £38/kWh) decreases with increased capacity. The benefit is saturated when self-consumption is fully achieved. The value of ES is influenced significantly by the coincidence level of the peak demand and output of renewables installed in the premise. This implies that in this application, ES would compete with demand response technologies.

Another application of ES is for the carbon footprint minimization. Our studies demonstrate that ES is charged during the low-emission periods and discharged during the high-emission periods. By using this operation strategy, the annual carbon footprint is reduced by 10.5% even with the increased annual energy consumption due to losses.

Due to relatively high costs associated with current ES technologies, reviewed technologies do not appear to be cost-effective in the present power system. The most effective technologies today are Li-ion battery (£480/kWh) for kW/kWh application and NaS (£230/kWh) for 100's kW/kWh application, both of which are much higher than the value (£100/kWh) quantified in the present system. However, with the expected reduction of the costs and significantly increased value (£280/kWh - £860/kWh) in the future system, some technologies such as (Li-ion, Vanadium flow, NaS, ZEBRA, Advance lead acid) may become attractive. Zinc air remains a promising low cost option, but still struggles to deliver a high cycle life. NiMH (610-1100 £/kWh) appears to be a high-cost option for ES, even in the future system.

Acknowledgements

We are grateful to EPSRC for supporting fundamental research, through Energy Storage for the Low Carbon Grids project that led to the development of the new electricity modelling framework that was used in this study.

Reference

Akhil, A. A. et al., 2013. *Energy Storage Handbook ,* s.l.: SANDIA.

Black, M. & Strbac, G., 2007. Value of bulk energy storage for managing wind power fluctuations. *IEEE Trans. Energy Convers,* Volume 22, pp. 197-205.

Byrne, R. H. & Silva-Monroy, C. A., 2012. *Estimating the Maximum Potential Revenue for Grid Connected Electricity Storage: Arbitrage and Regulation,* Sandia National Laboratories: SAND2012-3863.

Chatzivasileiadi, A. & Eleni Ampatzi, I. K., 2013. Characteristics of electrical energy storage technologies and their applications in buildings. *Renewable and Sustainable Energy Reviews,* Volume 25, pp. 814-830.

Elexon, n.d. *http://www.elexon.co.uk/.* [Online].

Energy Research Partnership, 2011. *The future role for energy storage in the UK*

Ferreiraa, H. L. et al., 2013. Characterisation of electrical energy storage technologies. *Energy,* Volume 53, pp. 288-298.

FICO, n.d. *FICO Xpress optimization suite.* [Online]
Available at: http://optimization.fico.com

Gill, S., Barbour, E., Wilson, I. & Infield, D., 2013. Maximising revenue for non-firm distributed wind generation with energy storage in an active management scheme. *IET Renewable Power Generation,* 7(5), pp. 421-430.

IEA, 2013. *World Energy Outlook 2013,* s.l.: IEA.

Karangelos, E. & Bouffard, F., 2012. Towards Full Integration of Demand-Side Resources in Joint Forward Energy/Reserve Electricity Markets. *IEEE TRANSACTIONS ON POWER SYSTEMS,* 27(1), pp. 280-289.

Kintner-Meyer, M. et al., 2012. *National Assessment of enegy storage fir grid balancing and artitrage Phase 1,WECC,* s.l.: PNNL.

Pudjianto, D., Aunedi, M., Djapic, P. & Strbac, G., 2014. Whole-Systems Assessement of the Value of Energy Storage in Low-Carbon Electricity Systems. *IEEE Trans.SMART GRID,* 5(2), pp. 1098 - 1109.

Sioshansi, R., Denholm, P., Jenkin, T. & Weiss, J., 2009. Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy Economics,* Volume 31, p. 269–277.

stoRE, 2013. *Facilitating energy storage to allow high penetration of intermittent*.

Strbac, G. et al., 2012. *Strategic Assessment of the Role and Value of Energy Storage Systems in the UK Low Carbon Energy Future,* London: Carbon Trust.

Sturt, A. & Strbac, G., 2012. Efficient stochastic scheduling for simulation of wind-integrated power systems. *IEEE Trans. Power Syst.,* 27(3), pp. 323-334.

Tuohy, A. & O'Malley, M., 2011. Pumped storage in systems with very high wind penetration. *Energy Policy,* Volume 39, p. 1965–1974.

Wong, S. & Fuller, J. D., 2007. Pricing Energy and Reserves Using Stochastic Optimization in an Alternative Electricity Market. *IEEE Trans. Power Syst.,* 22(2), pp. 631 - 638.