Role of large scale storage in a UK low carbon energy future

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Abstract

Large scale storage offers the prospect of using excess electricity within a low carbon energy system, which otherwise might have to be curtailed. However the economics only become favourable for large penetrations of renewable generation. A model has been developed to simulate the cash flow of selected large scale storage technologies inside a future UK low carbon energy system, based on historical data for electricity demand and projected renewable resources. The results show that, despite their relatively low round trip efficiency, both compressed air energy storage and hydrogen storage could become potential candidates for large scale storage because of their low energy related storage costs. The direct comparison with combined cycle gas turbines shows that, under certain assumptions, storage could provide a competitive alternative to peaking plants with low load factors. Uncertainty surrounding the returns of storage applications may require policy support for a successful strategic deployment of storage within the UK energy system.

Key words: Large Storage, Energy system modelling, Intermittent generation, Storage economics

1. Introduction

The transition towards a low carbon future requires an unprecedented change to the way in which we generate, distribute and use energy. Current scenarios for the UK broadly agree that in order to achieve an overall greenhouse gas emissions reduction target of 80% by 2050, the power sector in particular will have to be decarbonised almost entirely (DECC, 2009; Ekins et al., 2009). Such a transition depends on a large scale deployment of low carbon technologies, such as nuclear, renewables and, once proven on a commercial scale, carbon capture and storage (CCS). The extent to which nuclear and CCS can offer flexible generation is not yet sufficiently understood (DECC, 2010). Hence, even low-carbon generation portfolios are expected to include substantial reserve capacity in the form of combined cycle gas turbines (CCGT) to balance the system. (Ekins et al., 2009)

Recent studies suggest that large penetration of variable and inflexible generators on the energy system will lead to increased volatility in electricity prices, with peak prices expected to exceed 1000 £ MWh^{-1}, whilst at other times prices could become negative. The peak prices will support reserve capacity operating at reduced load factors, whilst negative electricity prices are said to be necessary to encourage generators to reduce output or for additional load to come online (Cox, 2009; Green and Vasilakos, 2010). Already today UK National Grid is preparing to bid down wind, and on 30 May 2010 successfully offered two wind farms £180 per MWh of reduced output. (Bailey, 2010)

Smart grids offer one option to improve system flexibility. They could encompass the management of grid connected electric vehicles (EV) and enable demand side management (DSM) of electric appliances, including ground source heat pumps, air conditioning units and industrial refrigerators, thereby acting as virtual storage. The combined UK potential of these flexible demands is estimated to amount to a not insignificant 10.9 GW (Welch, 2010). However, the duration over which these measures can displace energy consumption is typically well below 10 hours.

Studies on storage in systems with high penetration of wind have identified the need for short term balancing (Black and Strbac, 2007; Bathurst and Strbac, 2003). Storage offering fast response is already a viable proposition, with current large scale storage facilities relying on income from ancillary services, such as reserve and frequency response. Pumped hydro power stations in Dinorwig and Ffestiniog, although capable of several hours of storage, trade actively in markets that suit their fast response times (Boon, 2010; Black and Strbac, 2007).

The volatility of electricity prices established by Cox points towards a market for storage beyond the short term balancing. The extent to which longer storage durations are desirable in a low carbon energy system is therefore the focus of this study. Further, the availability and economic feasibility of storage technologies to suit the system requirements will be assessed.

Currently storage is not treated as a critical component of a future energy system by policy makers (DECC, 2010). This study aims to identify whether large scale storage in the UK can become economically viable and if policy support as part of a strategic development towards a low carbon electricity system is likely to be desirable or necessary.

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2. Modelling approach

The characteristics of the UK wind resource and its impact on the electricity system are relatively well researched (Gross et al., 2006; Sinden, 2007). Further studies have explored the use of storage in connection with renewable energy systems (van der Linden, 2006; Solomon et al., 2010; Exarchakos, 2008; Wilson et al., 2010; Weber, 2005), often with a focus on isolated systems. This study specifically choses to model the integration of storage into the grid, as suggested by Korpas and Gjengedal (2006); Barton and Infield (2004) and Anderson and Leach (2004).

The UKERC 2050 project has developed scenarios, building on a holistic and system wide approach. Their pathways have been developed with support of the UK-MARKAL model, a technology rich market allocation optimisation model. The MARKAL model represents time as 6 distinct time zones (day and night for summer, winter and intermediate respectively).

Other studies have used high temporal resolution to understand system balancing with high penetration of wind and issues arising from ramp and slew rates of wind and errors in wind forecasting. (Black and Strbac, 2007, 2006; Pelacchi and Poli, 2009; Barton and Infield, 2004; Bathurst and Strbac, 2003)

The model used in this study is positioned between the two approaches above. It draws on historical data with high temporal resolution (half hourly to hourly), but at the same time covering a long period of 6 years. This approach aims to identify the scale and scope for storage extending beyond short term balancing as a strategic component of a future energy mix.

Both wind and solar PV are considered as renewable sources of energy. For simplicity and computational reasons many other aspects of the model comprise reduced detail. Since the ‘need’ for storage is initially an economic question (Denholm et al., 2010), this model is primarily concerned with the commercial value of storage from an investors perspective. Other benefits, such as carbon saving, energy security and deferral of investment in other parts of the energy system, to name but a few, should be included in any subsequent assessment of appropriate policy support instruments for storage deployment.

Fig. 1 gives an overview of the model structure. Time resolved data for meteorological resources and power demand form the basis for the decision to charge (buy) or discharge (sell) storage. The operating strategy is to provide arbitrage, by buying at low prices and selling at high prices, without other strategic trading. From the flows in and out of storage and the cost of the installation, a cash flow is established. The configuration of the storage capacity and power, which feeds into the cash flow, also provides constraints to the operation of the storage system. A solver therefore optimises the configuration for maximum net present value (NPV). The NPV method has been chosen over a levelised cost approach, to ensure that investment risks arising from changes in revenue can be reflected. (Anderson, 2007)

For analytical simplicity, the UK network is assumed to be a single bus system (’copper plated island’), meaning that demand can be met by generation, independent of their physical locations and free of network constraints or losses. For the purposes of storage assessment this assumption provides a worst case, since transmission and distribution constraints can be expected to make storage more favourable during times of congestion between regions. During the simulation the plant mix remains static. Investment in technologies other than storage is beyond the present scope of this model.

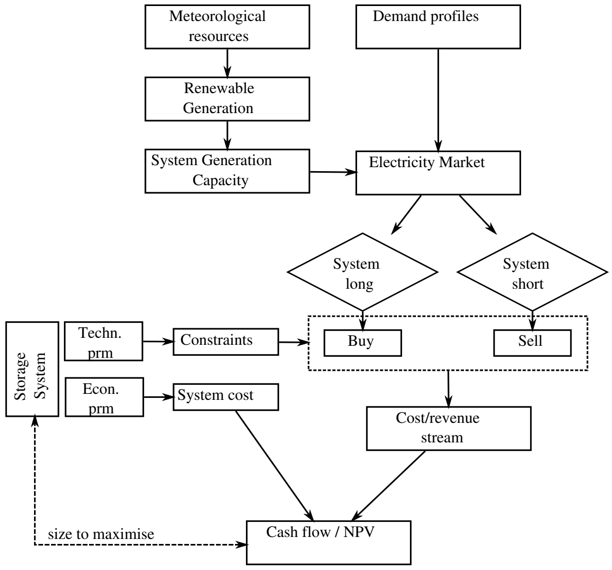

Figure 1: Flow chart of the storage model. A time series of storage charge and discharge is built up from renewable resource and demand data. The NPV is calculated from costs of a given storage system and the revenues from operation within the constraints for power and energy capacity.

2.1. Input data

Two main sets of data are used to establish the system balance over time. Firstly, information on historical UK electricity demand for a duration of 6 years (2003-2009) with half hourly resolution is available from the National Grid (National Grid, 2010). Secondly, the output from renewable installations is established from meteorological data for 16 sites throughout the UK for the same period (UK Meteorological Office, 2006). Data are mostly recorded hourly. In some instances interpolation has been necessary to account for the occasional missing reading.

The demand data have a mean of 36.3 GW and a peak of 59.9 GW, such that a conventional power system with 20% capacity margin can be assumed to be sized to about 72 GW. The demand data have not been scaled to account for possible increases or decreases in electricity demand.

Wind speeds were originally recorded at a height of 10 m above ground, and were scaled up to suit a hub height of 50 m as

$$u_{50} = u_{10}\left(\frac{50\,m}{10\,m}\right)^{p} \tag{1}$$

where u_x is the wind speed at height x. The value for p depends on surface roughness and is assumed to be 0.1429 (Best et al., 2008). Wind speeds are converted using power curves for commercially available wind turbines. No assumptions have been made for their possible improvement over the the next decades. The mean capacity factor of 33%, achieved with this method, has been found to be broadly consistent with other studies (Zervos and Kjaer, 2008). Wind power is assumed to make up 70% of the UK's installed renewable energy resource.

Solar irradiance data were recorded as the duration of direct irradiation within each hour. Intermittent irradiation on a partially cloudy day can be misread as continuous sunshine, overestimating irradiance by up to 20%. Similarly, diffuse sunlight that is not recorded, may still lead to PV output. Data was consequently scaled to meet the expected UK average irradiation of about 1100 Wh m^{-2}. (Šúri et al., 2007; UK Meteorological Office, 2006)

The use of historical data ensures that any correlation between weather patterns and energy consumption is adequately reflected, and their chronology is preserved. The data, covering 6 successive years, will be used to highlight issues arising from stochastic variations between years.

2.2. *Economic characteristics of storage technologies*

A range of large storage technologies find mention in the literature. Some are well established (e.g. pumped hydro), whilst others offer novel solutions, such as recently proposed gravel batteries (see Isentropic (2010); Garvey (2010)). This study limits the choice of technologies to those that enable long storage durations, suit large scale deployment in the UK and are techno-economically sufficiently well characterised. For more detail on storage technologies, see Amos (1998); Cavallo (2001); Eckroad (2002); Townsend (2009); Schoenung (2008); Haubrich (2006); Walawalkar and Apt (2008) and Electricity Storage Association (ESA) (2010).

The costs of different storage technologies vary significantly, with particular discrepancies between the costs related to the power and the costs related to its energy storage potential as shown in Fig. 2. The range represented by their surrounding boxes reflects differences in assumptions on type and scale of application, learning rates and in some cases a lack of robust cost data due to the limited experience with these technologies.

Since this study is concerned with the deployment of large scale future applications, the assumptions tend to be towards the lower end of literature estimates. To assess the role of storage within the energy system we need to further consider some of the technical and operational characteristics of these technologies. Table 1 gives an overview of assumed costs and properties of selected technologies.

Both compressed air energy storage (CAES) and hydrogen storage rely on suitable geology, with underground salt caverns offering the cheapest option. The energy related cost of these technologies depends on the state of development of these sites. (Evans and Holloway, 2009; Plaat, 2009; Howard B. J. Stone and Richardson, 2009)

Since this study is aimed at storage applications, where the energy to power ratio is high, Fig. 3 gives the normalised system costs for different storage durations. The term storage duration (τ) is used in this context as the ratio between the amount of energy a system can store and the power at which the energy can be delivered. It could be seen as the theoretical minimum time to fully discharge a full storage reservoir. It is hence not necessarily related to the duration energy remains in storage.

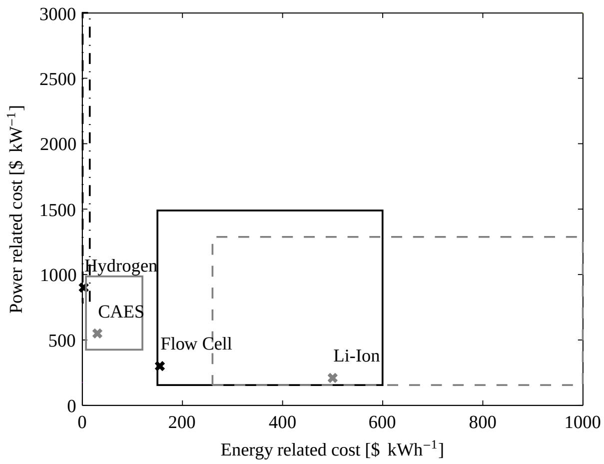

Figure 2: Costs for power storage technologies, split into power and energy related costs. The range of estimates found in literature is represented by the boxes. The costs assumed in this study are marked with 'x'.

Table 1: Storage property assumptions for selected technologies. Based on Amos (1998); Cavallo (2001); Eckroad (2002); Townsend (2009); Schoenung (2008); Haubrich (2006); Electricity Storage Association (ESA) (2010)

Property	**LiIon**	**Flow**	**CAES**	**H$_2$**	**unit**
Energy cost (C_E)	500	70	25	4-8[a]	\$ kWh^{-1}
Power cost (C_P)	225[b]	600	550	1200	\$ kW^{-1}
Efficiency (η_{sys})	90	75	72	35	%
Lifetime (L)	600	1500	6000	1800	cycles [c]

[a] Depending on the state of development of underground storage facilities. [b] LiIon batteries have an energy to power ratio of about 0.45 h. Costs are a function of either C_E or C_P. [c] A cycles is defined as 80% depth of discharge (DoD)

For increasing values of τ, CAES, flow batteries and hydrogen become least cost installation options in that order. However, in the same order, the systems also exhibit decreasing efficiency.

In the current energy system, where the value of electricity is high and volatility mostly upwards, efficient use of this high grade energy vector is of high priority. Hence, storage technologies with low round trip efficiency tend to be disregarded for commercial applications (Townsend, 2009; Scherer and Newson, 1998; Schaber et al., 2004).

For a low carbon energy system, however, this proposition may not apply in the same way. Once the amount of electricity from renewables increases, the value of electricity becomes more volatile upwards as well as downwards, as shown by Cox (2009). Any renewable energy that has to be curtailed, undergoes an effective conversion efficiency of 0%. At this point even a conversion chain with low efficiency may improve the overall system efficiency. Such conversion chains could therefore also include thermal storage from electricity, as suggested by the ECCC (ECCC, 2010), or hydrogen storage, as proposed by

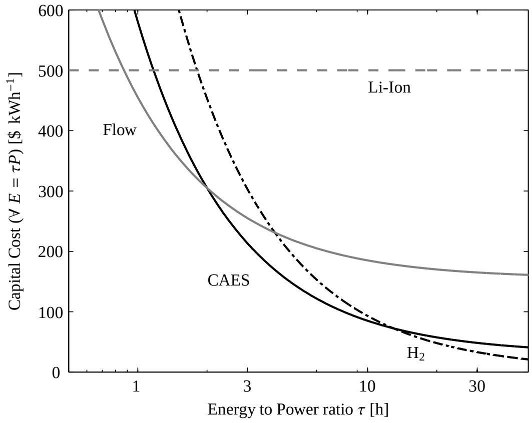

Figure 3: Capital cost of power storage technologies for a given energy to power ratio (τ).

Barton and Gammon (2010).

2.3. Storage economics

The economics of a storage plant are mostly analogous to those of a conventional plant, with the notable difference that the primary energy (E_{in}) is traded in the same market as the final product (E_{out}). The profitability of a storage investment therefore depends not on a 'spark-spread', as given by the difference between gas and electricity price, but the spread between the price of electricity at the time of charging (π_{in}) and discharging (π_{out}). We shall call this the π-spread

$$\Delta\pi = \pi_{out} - \frac{\pi_{in}}{\eta_{sys}} \tag{2}$$

for a system with a round trip efficiency of η_{sys}. The total amount of energy delivered from a storage installation is

$$E_{out} = c \times E \times DoD \times \eta_{out}$$

where c is the number of charge/discharge cycles per year, E is the installed storage capacity, DoD is the mean depth of discharge per storage cycle and η_{out} the discharge efficiency. For a given amount of energy output, the energy required to charge the system is

$$E_{in} = \frac{E_{out}}{\eta_{in} \times \eta_{self}^{\Delta t}}$$

where the product of charge efficiency (η_{in}), discharge efficiency (η_{out}) and self discharge losses with storage duration from $\eta_{self}^{\Delta t}$ make up the total round trip efficiency of the system

$$\eta_{sys} = \eta_{in} \times \eta_{out} \times \eta_{self}^{\Delta t} = \frac{E_{out}}{E_{in}} \tag{3}$$

The capital cost of a storage system (C) is calculated from the energy related costs (C_E) and the power related cost (C_P) for a given technology. Some scale independent fixed costs (C_{fix}) may also be incurred. Given the scale of the systems considered here, these fixed cost can be negligible in comparison.

$$C = C_{fix} + C_E \times E + C_P \times P$$

For a storage system to be economically viable, a positive NPV has to be achieved from

$$\sum_t (1+r)^{-t} \left(\pi_{out} E_{out} - \pi_{in} E_{in}\right) - C \geq 0 \tag{4}$$

Due to the strategic nature of investment in storage, this study uses a moderate discount rate of 6% and an economic lifetime of 20 years.

With the discount factor (a) given by the economic life time (n) and the discount rate (r)

$$a = \frac{(r+1)^n - 1}{r(r+1)^n} \tag{5}$$

and the π-spread definition (2), the condition 4 can be simplified to

$$\Delta\pi E_{out} - \frac{C}{a} \geq 0 \tag{6}$$

As shall be shown later, the implicit assumption (common for conventional plant) that $\Delta\pi E_{out}$ is consistent over years, requires further scrutiny, because utilisation changes depending on demand patterns and the renewable resource of each year. Secondly, the π-spread depends on system efficiency. Unlike for coal or gas plants, where standard efficiencies are used to calculate spark-, dark- or clean-spread, storage technologies are more diverse, as shown in table 1. The economic importance of efficiency depends on the expected price of electricity. From (6) and (2) the minimum efficiency condition for a positive NPV can be written as

$$\frac{\pi_{in}}{\pi_{out} - \frac{C}{aE_{out}}} \leq \eta_{sys} \tag{7}$$

which suggests, that for a system operating on low cost excess electricity, the efficiency can be somewhat lower. It should be noted, however, that with low efficiency, more storage capacity is required to deliver the same E_{out} and thus the system costs increase. The exact relationship between storage capacity and the energy delivered from storage depends on the environment in which the storage system operates. The time resolved approach described in Section 2.4 will be used to this end.

2.4. Storage time series

Storage is represented as a time series of energy flows for 30 min periods (Δt). Positive flows feed into storage, whilst negative flows represent energy removed from storage. The flow, $f_{(t)}$, is constrained by the power P of the storage system

$$-\frac{P}{\eta_{out}} \leq f_{(t)} \leq P \times \eta_{in}$$

The amount of energy flowing in and out of storage in each time period is further limited by the storage level at the time, $S_{(t)}$, which is constrained between 0 and the storage capacity E.

$$f_{(t)} = \begin{cases} min\left((E - S_{(t-1)})\Delta t^{-1}, \Delta P \times \eta_{in}\right) & if\ \Delta P > 0 \\ -min\left(S_{(t-1)}\Delta t^{-1}, -\Delta P \times \eta_{out}^{-1}\right) & if\ \Delta P \leq 0 \end{cases}$$

where ΔP is the external grid request to provide load ($\Delta P > 0$) or power ($\Delta P < 0$). From this flow the storage content can be developed as a time-series with

$$S_{(t)} = S_{(t-1)} \times \eta_{self} + f_{(t)} \times \Delta t$$

The flow can be seen as a storage internal process. For the external world the power used and delivered by storage (P_{str}) is more relevant.

$$P_{str}(t) = \begin{cases} f_{(t)} \times \eta_{in}^{-1} & if\ f_{(t)} > 0 \\ f_{(t)} \times \eta_{out} & if\ f_{(t)} \leq 0 \end{cases}$$

Ultimately, the performance of storage is measured by the total energy delivered

$$E_{out} = \sum_{t} P(t) \times \Delta t \ \ \forall\ P(t) > 0$$

2.5. Dispatch strategy and price setting

The energy system is modelled around four types of generators, characterised by their operating strategy and ability to dispatch energy. The following list describes their position in the merit order.

Uncontrolled / variable generators: Most renewable technologies are characterised by high capital and low running costs. They will therefore aim to dispatch their energy whenever possible. With additional policy incentives for generation, some of these technologies may still choose to generate even at negative electricity prices. Other than curtailment, their output is not influenced by the system.

Inflexible / baseload generators: Nuclear power stations choose for technical as well as economic reasons to operate at high and consistent load factors. Fossil fuel powered thermal plants would, if possible, operate at a consistent high output, too. This improves their efficiency and hence, their CO_2 emissions factor. Baseload generators, as defined in this model, are therefore the sum of output that would choose to stay on the system, even during a temporary drop in electricity prices.

Flexible generators: These can respond to changes in demand more quickly and cheaply than the storage technologies considered here. This can include flexible portions of the baseload generators, i.e. their spinning reserve. Technically this can also include any of the short duration storage solutions, such as grid connected electric vehicles or DSM, mentioned in section 1.

Peaking plants: Generators that are required on the system to ‘keep the lights on’. These may well operate under economically unfavourable conditions. Their load factors may be low and the need to respond to sudden changes in demand could require fast ramping. These plants depend on the financial incentive of temporally high electricity prices to be kept on the system.

The position of storage within this merit order changes depending on the state of the system. An example of the generation and demand profiles over a 10 day period is shown in Fig. 4. A total of 20 GW of baseload capacity is complemented by 5 GW of flexible generation. The amount of peaking plant is sized to suit the demand after renewables and storage. When the system is long (i.e. the sum of variable and baseload generation exceeds demand) no other generation occurs and storage offers additional load, before baseload or variable generators have to curtail their output. Conversely, if the system is short, flexible generators dispatch energy, before storage and finally peaking plants are called up.

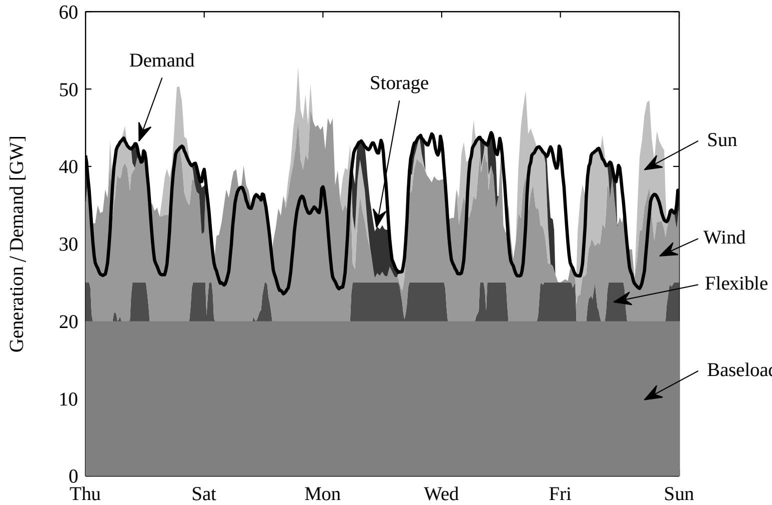

Figure 4: Extract of model data for a 10 day period of generation and demand profiles. When generation exceeds demand, surplus energy can be stored until it is fed back during times when the system is short. The white areas below the demand line have to be met by peaking plants.

The marginal costs of inflexible plants are not well understood, not least because the technical potential of such plants to operate flexibly is not fully explored. For the purposes of this model the marginal cost of inflexible plants is assumed as 10 £ MWh^{-1}. At this price an inflexible plant can sell excess electricity to a storage load. The price at which storage can sell energy to the system is framed by the marginal costs of flexible and peaking plants. A mean value of 80 £ MWh^{-1} has been assumed.

2.6. Alternatives to storage

It has been suggested that for utility companies to embrace investment in storage technologies, the case has to be made with respect to the current business model of curtailing excess wind and meeting any negative imbalances from thermal reserve plant, with combined cycle gas turbine (CCGT) plants being the current reference technology of choice. (Mack, 2010; Denholm et al., 2010)

Another investment alternative could be the installation of further interconnects with the European mainland. The commercial comparison here includes uncertainties in exchange rate and electricity market prices in Europe. In particular the extent of any future correlation in electricity prices between the UK and other European countries, for instance in the presence of large weather systems, puts this evaluation outside the scope of this study.

The condition, which storage has to meet to be regarded viable with respect to a CCGT plant, can be derived from (4) for both technologies

$$\begin{aligned} NPV_{CCGT} &= \textstyle\sum_t (1+r)^{-t} \left(\pi_{out} E_{out} - \pi_{gas} E_{in}\right) - C_{CCGT} \\ NPV_{str} &= \textstyle\sum_t (1+r)^{-t} \left(\pi_{out} E_{out} - \pi_{in} E_{in}\right) - C_{str} \\ NPV_{str} &\geq NPV_{CCGT} \end{aligned}$$

where π_{gas} is the gas price.

If their levelised cost were equal, both would dispatch at the same position in the merit order, i.e. they are competing for the same market. For arguments sake, we shall further assume that the operation and maintenance costs and the costs related to the power (C_P) are identical for both systems. Thus, storage carries additional cost for its storage capacity.

Rewriting the energy delivered in terms of a load factor (L) and the energy to power ratio of storage again as τ, results in the following condition

$$\left(\frac{\tau C_E}{aL \times 8760h} + \frac{\pi_{in}}{\eta_{str}}\right) \leq \frac{\pi_{gas}}{\eta_{CCGT}} + \pi_{CO_2} \qquad (8)$$

where η_{CCGT} is the efficiency of the CCGT plant and π_{CO_2} is the cost of emitting or capturing CO_2 per unit out output energy. Whilst the efficiency and costs can be estimated, the load factor will be established from the storage model.

3. Economic value of storage

The NPV over a 20 year period has been extrapolated from 6 years of historical data using the model described in 2. The penetration of renewables is steadily increased, to simulate the performance of each of the selected technologies in turn. Fig. 5 shows the mean NPV based on the entire data set. The error bars represent the standard variation observed between individual years.

For systems with low penetration of renewables, none of the large scale storage technologies are economically viable. However, as the amount of variable generation increases, the economics of storage improve. CAES is the first technology to become beneficial at around 40 GW of total installed renewables. For larger penetration of renewables hydrogen also becomes a contender. As the amount of renewables increases further, the returns for storage start to diminish. In these cases ample supply of excess electricity is available, but not enough periods in which these can be fed back into the system occur.

The configuration of the storage system is optimised for maximum NPV. In a system with 60 GW of installed renewable generation (42 GW wind, 18 GW PV), a flow battery system is sized to 21 GWh of storage capacity, whereas CAES and hydrogen would ideally be sized at 68.9 GWh and 314 GWh respectively. The power for such systems ranges between 1.5 GW (Flow Battery) and 3.9 GW (CAES).

From a system transition pathways point of view, the technical similarities between CAES and hydrogen storage may offer an option to develop underground salt caverns for CAES initially, but to switch sites to hydrogen storage over time, thereby forming an organic growth path for the development of a hydrogen system. This transition would not only increase the total available storage capacity, but further reduce CO_2 emissions, since CAES itself still involves the use of gas turbines.

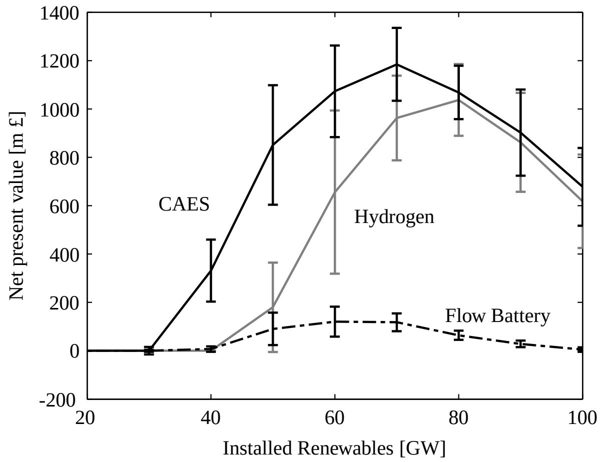

Figure 5: Mean NPV for storage technologies based on historical data for 6 years. Error bars represent standard variation between different years of data.

3.1. Load profiles

Load factors for this type of storage application are inherently low. Firstly, for about half the time the system has to be available for charging. Secondly, for any system with high storage duration, the load factor is further reduced, because the number of charge and discharge cycles is limited.

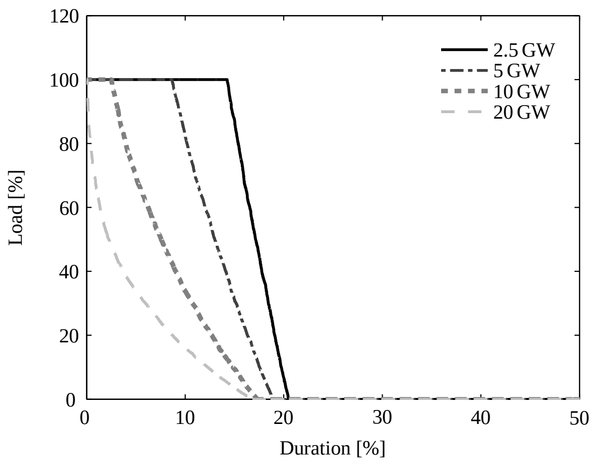

Figure 6: Load-duration curve for the storage discharge side. Load factors are less than 20% and decline sharply for larger installations.

Fig. 6 shows load duration curves for a system with different power ratings over a 12 month period. In the modelled environment the time that these systems can operate at their rated capacity reduces sharply for installations with more than 5 GW. This explains why the optimisation model did not choose configurations exceeding 6 GW for any of the cases investigated.

3.2. *Comparison with CCGT*

The relationship in eq. 8, set out to compare the probability for storage to offer a higher investment value than CCGT, based on the load factor. Since many of the input parameters, including the load factor itself, are uncertain, a Monte Carlo approach has been chosen. In the absence of a stochastic model, the load factors have been assumed to be normally distributed. The standard deviation within the data available has been established as 1.37 with a mean of 14.64%. Other parameters are assumed as evenly distributed, such as the electricity price (π_{in}) between 5 and 15 £ MWh^{-1}, and the values for hydrogen storage listed in table 1.

Fig. 7 shows the probability distribution, based on 100,000 data points. The levelised running costs of CCGT include the fuel price per unit of output. Any costs associated with CO_2 abatement or trading should also be seen as part of these costs. At about 56 £ MWh^{-1} the probability of storage to outperform CCGT reaches its 50th percentile.

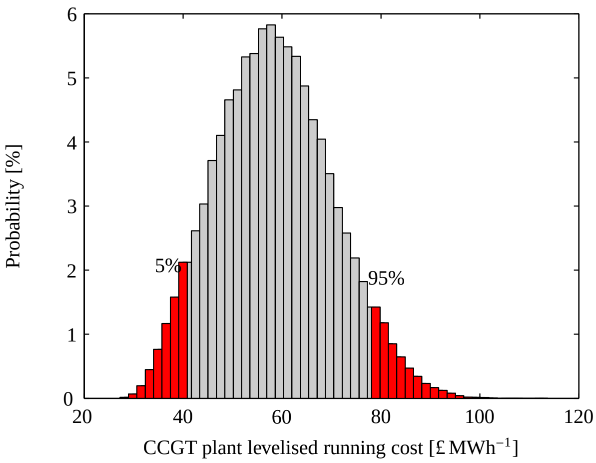

Figure 7: Probability distribution of storage being economically favourable to CCGT plants. Assumptions: π_{in} evenly distributed between 5 and 15 £ MWh^{-1}, storage properties for hydrogen case, load factor based on modelled distribution.

4. Sensitivity analysis

The viability of storage hinges on a large number of interdependent variables. In the above cases the theoretical viability has been established. However, changes in the assumption can significantly affect the results, as shown in Fig. 8. Here, a base case scenario is subjected to changes for individual input parameters, providing a snapshot of their impact on NPV.

Amongst the most sensitive parameters is the π-spread. Its value is sensitive to the electricity market arrangements and the costs structure of the plant mix. More work, especially on the role of nuclear and CCS in delivering flexible generation, is needed to better understand the uncertainty surrounding the π-spread.

The relative importance of discharge efficiency is confirmed. The NPV is more sensitive to changes in discharge efficiency compared to charge efficiency, due to the higher value of electricity at times of selling to the grid.

The economic parameters are two further critical assumptions. As with most sustainable technologies, the up-front costs are high, and the returns spread over many years. A long-term view is required. Internal rates of return of 10% with pay-backs of less than 20 years are unlikely to be met by such systems.

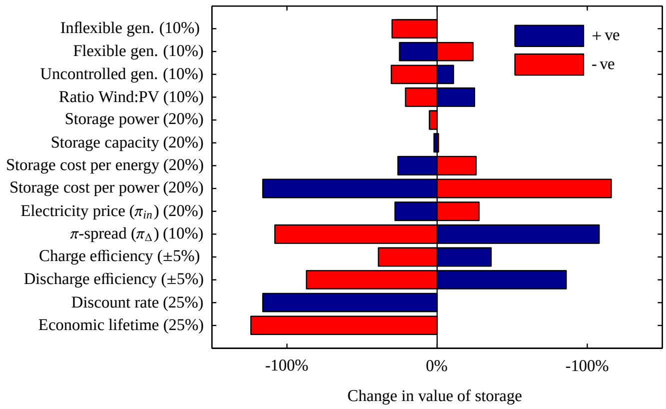

Figure 8: Sensitivity response of the value of storage to changes in input parameters. Changes to the base case are noted in brackets. These are relative unless marked as '±'.

4.1. *Stochastic uncertainty of economic returns*

Alongside the uncertainty surrounding some of the parameters mentioned in the previous section, storage is also subject to stochastic variations in demand and the availability of renewable resources. The scope for establishing the probability distribution of economic returns using historical data is limited. Nevertheless, returns on investment for each of the 6 years of data can be established. One year is the shortest period for which most periodic effects can be assumed to be included. Each year is simulated with identical storage installations to compare their returns. The results show that year-on-year returns are by no means consistent. Analysis of the reason for the variations shows no strong correlation with the total demand or amount of renewable resources in each year, nor does it follow any strong pattern with the difference between the two.

The returns of storage must depend therefore on the distribution in time, which these profiles follow. To establish if there is such a thing as a 'good' or 'bad' demand profile, or if returns are more affected by changes in the renewable resource, we suspend the temporal link between the two sets of data, and simulate demand data of one year with the renewable resource data of another.

Fig. 9 gives some indication as to the likely causes of storage performance. The six years with the temporal link intact, are

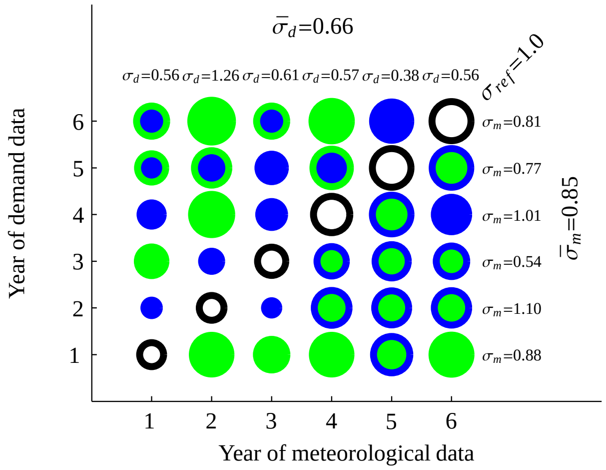

Figure 9: Year on year variability of storage economics. Black rings are the years where time consistent data was used, ranked by economic performance. The size of circles scales with economic performance. Coloured rings compare to the reference demand year (black circle in this column), and the inner colour compares to the reference meteorological year (black circle in this row), with light/green being better and dark/blue representing poorer performance.

ranked by storage performance, with one being the poorest, and six the one with the highest returns for storage. These form the diagonal in the graph. The returns are represented by the size of the circles. Each column shows the returns using the meteorological data for the same year, but meeting the electricity demand of different years, and vice versa for each row. If there was such a thing as an inherently unsuitable profile, one would expect to find an overall trend towards good performance in the top right of the graph and poor performance in the bottom left corner. Similarly, if certain years were unsuitable for storage, due to the demand or the meteorological resource alone, this trend would show up as rows or columns that are consistently worse than their reference cell on the diagonal. Such a trend is not very pronounced, with some of the best results found in row 1 and column 2 (i.e. the poorest reference years).

To better understand the source of uncertainty for storage investments, the standard deviation, normalised to the standard deviation of the reference years, has been included for each row and column. It is apparent that the variation is on average lower across different years of demand data. Or in other words, the uncertainty of returns in a storage investment is caused to a greater extent by changes in the renewable resource, rather than changes in the demand profiles. This may not be entirely surprising (weather being more erratic than people's demand patterns). Between the two, however, it is the influence that is somewhat more outside policy makers' control.

The assertion that renewable resources and demand profiles are weakly, but positively correlated can be confirmed within this set of data. Consequently the storage utilisation is higher on average, when using data from two different years, compared to temporally consistent sets. For further statistical analysis of storage from renewables, this link between meteorological data and demand profiles should be reflected.

5. Summary and conclusions

Storage is uniquely able to utilise excess generation that would otherwise have to be curtailed. It thereby improves the overall system efficiency for systems with a high penetration of renewable energy.

Both CAES and hydrogen storage offer potentially attractive future options for large scale storage. Due to their low energy related capital cost, 4 GW systems have shown to provide economically optimal storage capacity of about 70 GWh or 310 GWh respectively. Whilst CAES appears to be economically favourable , the larger capacity offered by hydrogen storage may provide wider system benefits, concerning CO_2 emissions, energy security and grid development, which have not been within the scope of this study. A possible transition path from CAES to hydrogen storage can be envisaged to support increasing demand for storage capacity over time.

The comparison with CCGT peaking plants has shown that storage becomes economically favourable, only if gas and CO_2 prices were to rise. However, the investment decision in storage may further be impeded by the uncertainty surrounding the returns. Even once technical and cost risks are covered, storage economics depend on a large number of uncertain factors. Some of these are outside the influence of policy makers, such as the stochastic variation in the demand for storage. Other sources of uncertainty, such as electricity balancing and pricing arrangements, or any measures affecting the generation plant mix, can be influenced by policy makers, and their effect on storage should be considered. It can be expected that policy support for storage is both necessary and desirable throughout development, demonstration and deployment phases.

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