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# Maximising the value of electricity storage

Iain Staffell[a,*], Mazda Rustomji[b]

[a] Centre for Environmental Policy, Imperial College London, SW7 1NA, UK
[b] Energy Futures Lab, Faculty of Engineering, Imperial College London, SW7 2AZ, UK

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ABSTRACT

Grid-scale energy storage promises to reduce the cost of decarbonising electricity, but is not yet economically viable. Either costs must fall, or revenue must be extracted from more of the services that storage provides the electricity system. To help understand the economic prospects for storage, we review the sources of revenue available and the barriers faced in accessing them. We then demonstrate a simple algorithm that maximises the profit from storage providing arbitrage with reserve under both perfect and no foresight, which avoids complex linear programming techniques. This is made open source and freely available to help promote further research.

We demonstrate that battery systems in the UK could triple their profits by participating in the reserve market rather than just providing arbitrage. With no foresight of future prices, 75–95% of the optimal profits are gained. In addition, we model a battery combined with a 322 MW wind farm to evaluate the benefits of shifting time of delivery. The revenues currently available are not sufficient to justify the current investment costs for battery technologies, and so further revenue streams and cost reductions are required.



## 1. Introduction

The world's leaders have now pledged to limit global warming to well below 2 °C, which will require significant increases in the penetration of intermittent renewables, inflexible nuclear generation and carbon capture and storage, together with electrification of heat and transport sectors. This raises considerable challenges in operating future electrical grids both efficiently and reliably. Electricity storage, demand side response, flexible generation and interconnection all offer methods to alleviate these issues [1]. Currently, storage is proving too expensive to make a significant contribution. Whilst much work is being carried out to reduce costs and improve efficiencies, this paper explores how storage can maximise its revenues through operating in multiple markets. Previous works have (1) focused on optimising for a single revenue stream such as arbitrage, (2) use global optimisation tools on specific cases, and (3) typically require perfect or very good foresight of future prices.

This work takes an existing algorithm for arbitrage from the EnergyPLAN software by Lund et al. [2] and extends it to co-optimise the provision of reserve, which we show can increase storage revenue by an order of magnitude. A full mathematical description and an open source implementation in MATLAB are given as Supplementary material.

The following section evaluates the revenue streams available to storage (focussing on the British market), barriers to its uptake, and the various technologies available. Section 3 describes the algorithm to optimise the operation of storage for arbitrage, with or without reserve services, under perfect and no foresight of future spot market prices and reserve utilisation. Section 4 gives a demonstration of the algorithm, simulating lithium ion and sodium sulphur batteries operating in the British electricity market. The results evaluate the attainable profits and rates of return within the current UK market, together with a sensitivity analysis of various model inputs and an assessment of storage integrated with a wind farm.

## 2. Background and literature review

### 2.1. Sources of revenue for storage

Storage has the flexibility to operate within energy market, trading energy to gain from arbitrage, and in ancillary markets, offering reserve, power quality and reliability services. It can also be integrated with existing infrastructure: generators such as wind farms (to reduce balancing costs, time-shift delivery or manage

* Corresponding author.
*E-mail address:* i.staffell@imperial.ac.uk (I. Staffell).

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**Nomenclature**

| | |
|---|---|
| ArbOnly | The arbitrage only scenario |
| ArbAv | The arbitrage with availability (but no utilisation) scenario |
| ArbAvUt | The arbitrage with availability and utilisation scenario |

constraints); demand centres (to reduce network service charges, e.g. triad avoidance); or networks (deferring costly upgrades to transmission and distribution systems).

*2.1.1. The potential and future of arbitrage*

The spread between daily peak and off-peak electricity prices depends on a multitude of factors: the difference in fuel costs of baseload and peaking generation, the carbon price, the difference in peak and baseload demand, the penetration of renewables and flexible technologies [3]. Similarly, future electrification of heat and transport has the potential to increase or decrease the spread, dependant on the extent to which the demand is managed in terms of spreading the peaks [4].

Storage that relies on daily energy arbitrage is susceptible to changes in the daily spread. Renewables may affect the spread by reducing prices when their output is high [5]. Some storage schemes, such as pumped hydro with very large reservoirs, may be capable of arbitrage over longer timescales, perhaps taking advantage of weekly spreads which are driven by lower demand over weekends, rather than renewable penetration [6].

Wind or PV which coincides with peak demand can reduce the spread. This appears to be the case in Germany, where PV coincides with peak daytime demand and suppresses prices during the day, resulting in lower peak prices which now occur in the morning and evening [7]. British peak prices occur in the evening, and so PV may instead increase the daily spread. Wind power has a less systematic diurnal pattern, but the penetrations seen in Germany and Britain are now sufficient to cause negative electricity prices, and thus increase the daily spread.

Fig. 1 displays the average daily spread in Germany since 2002 (peak minus baseload price) as a proportion of the median spot price, against the growth of solar PV and wind penetration. Before the rise in PV capacity, the cost difference between coal and gas plants was the main driver [3]; however, since 2008, the spread has consistently reduced, as the penetration of PV has dramatically increased.

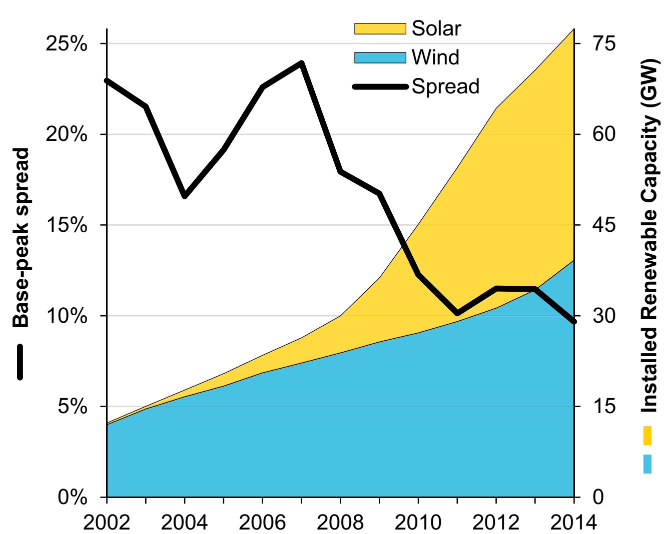


**Fig. 1.** Variation of average daily price spreads, gas-coal fuel price spreads and growth of wind and solar PV in Germany. Based on data from [3,7,8].

The daily demand profile varies significantly between countries. For example, the UK's peak demand is typically in the evenings, when solar is less likely to displace conventional generation. This greatly reduces its impact on the price spread, though it may still depress average wholesale prices.

*2.1.2. The structure of balancing services in the UK*

A second type of revenue that storage can access is from balancing services. In the UK, there are three types [9]:

- Ancillary and Commercial Services
- Contract Notifications Ahead of Gate Closure
- Bid – Offer Acceptances (also known as the 'balancing mechanism')

The first includes specific services that are contracted for in advance, namely reserve, response, power quality and reliability services. The income is typically based on utilisation volumes (MWh of energy) and/or availability offerings (MW of capacity). The second enables National Grid (Britain's transmission system operator) to contract directly with parties to purchase or sell electricity ahead of gate closure, typically when it predicts system imbalances may occur [9]; however, it is rarely used (most recently in 2012) and is hence not considered further [10]. The third type, the 'balancing mechanism', operated post gate closure (i.e. less than an hour ahead of real-time). Generators and consumers can submit bids to buy electricity (increase demand or reduce generation) and offers to sell electricity (reduce demand or increase generation), indicating the price at which they are willing to deviate from their preferred schedule [9].

The contracted nature of ancillary services results in income streams that are typically more predictable or at least offer some level of certainty, and hence these are considered further for the remainder of this study. Ancillary services consist of frequency response, reserve, black start and reactive power services [9]. In a broad sense, response services balance the power demanded with generation on a second by second basis, whereas reserve provides energy balancing during unforeseen events of longer duration, such as a tripped generator or incorrectly forecast demand. Black start is required in case of total or partial transmission system failure, to gradually start up power stations and link together in an island system. Finally reactive power services involve maintaining adequate voltages across the transmission network, though such a service may also be useful on distribution networks. A more detailed description of these is given in the online supplement.

*2.1.3. Short term operating reserve*

It is likely that storage has roles to play in all four elements of ancillary services; however, we focus on the provision of reserve, and specifically short term operating reserve (STOR) for reasons of data availability. STOR is a commercially tendered service, where a constant contracted level of active power (or demand reduction) is delivered on instruction from National Grid, typically when demand is greater than forecast or to cover for unforeseen generation unavailability. The service only requires participants to be available during predefined availability windows, with typically two to three occurring per day [11].

Participants are expected to deliver within 4 h of instruction (though most tenders could within 20 min), with a minimum capability of delivering 3 MW for 2 h, followed by a maximum 20 h recovery period [12]. In 2012/13, the majority of units were less than 10 MW in capacity, with typical utilisation times of 90 min

[12]. Providers are selected through competitive tenders based on economic value, historic reliability and geographic location [11]. Committed providers are expected to remain available for all windows over a season, meaning they cannot generate for other services (e.g. providing arbitrage).

*2.1.4. Current volumes of balancing services*

The volume of the British electricity market averages ~850 GWh per day, and peaks at a daily-average of 53 GW. For arbitrage on a daily level, an average of 67 GWh per day and up to 13 GW could be moved (from evening peak to overnight trough) before the diurnal profile was completely flattened. For reserve, STOR holdings of ~2.3 GW are currently considered optimal [13], with a mean daily utilisation of 0.69 GWh between April 2014 and March 2015 [14]. Optimal fast reserve holdings were typically ~300 MW [15], with a mean daily utilisation of 0.74 GWh throughout 2014/2015 [14]. Between November 2015 and March 2016, this has increased to 600 MW during the morning and evening.

Response holdings are dependent on total demand, the largest expected single loss of generation, and output of intermitted generation. Hence holdings are higher during summer and overnight, when demand is relatively low. Typical minimum daily holdings range between ~400 and ~700 MW for primary response, ~1200 and ~1450 MW for secondary response and ~0 MW and ~150 MW for high frequency response, dependant on time of year [16]. However diurnal variation is particularly significant for primary and high frequency response, where early morning summer requirements often exceed 1350 MW and 390 MW respectively [17].

*2.1.5. The current value of balancing services*

Response, reserve and reactive power services are remunerated for both availability (£/h) and utilisation (£/MWh). Services that include availability windows also receive window initiation payments (£/window) to compensate the participant for readying their plant prior to each window. The total annual spending on each service by National Grid typically ranges from £50 m to £150 m per year [18]. The market size for shorter timescale services (frequency response and fast reserve) is greater, suggesting storage with fast response times would have the potential to access greater revenue streams. This is in agreement with Strbac et al., who suggest shorter duration storage has much greater value [1].

*2.1.6. The future of balancing services*

Historically, the level of reserve services procured are set to cover three standard deviations of uncertainty, hence can accommodate over 99% of unexpected fluctuations [19]. The uncertainty is formed of error in both the forecast demand and supply. The latter includes unexpected plant outages, loss of the single largest generating unit, and imperfect forecasts for weather-dependent renewables output. Recent forecast requirements for primary and high response have approximately doubled [20,21], in preparation for larger units connecting to the system (new nuclear reactors and interconnectors) and in response to the dramatic increase in wind and solar capacity.

Intermittency increases the standard deviation of supply fluctuations, however the increase is only moderate due to smoothing of outputs up to an hour ahead, and good forecast accuracy up to several hours ahead [19]. The increase does however lead to greater demand for flexible products that can change output rapidly many times per day, as well as maintain a very low or zero standby level [22]. Yet increasing the holding of products such as STOR (of which 2.3 GW is currently considered optimal) may not be the most cost effective way to deal with intermittency [23]. Balancing requirements for wind continuously vary every hour, day or week, whereas STOR is fixed for an entire season. Hence in the future, this could lead to the introduction of new balancing services. A review by Gross et al. found six of seven studies quoting increases in overall reserve requirements of between 3 and 9% for a 20% penetration of intermittent generation [19]. It is worth noting, that current reserve required to cover wind and PV total about 17% of their output [24]. Other factors such as electrification of heat and transport may also have an effect by making demand more variable between periods and increasing forecast errors [22,25], together with an increase in power plant genset sizes resulting in higher response and reserve requirements [26,27].

*2.1.7. Alternative sources of revenue*

Further sources of revenue include integrating storage with generators, demand centres or networks. Generators such as wind farms may benefit by utilising storage to improve delivery forecasts and thus reduce balancing costs, and by shifting the time of delivery (effectively arbitrage) to sell for higher prices. This is particularly pertinent if wind penetration increases due to its effect on suppressing spot prices during periods of high national wind output [5]. Many wind farms currently operate under a power purchase agreement (PPA), which typically purchase all wind output at a fixed price [28,29]. This offers a price guarantee, at the expense of including a risk premium. Control over when electricity is delivered may enable better terms to be gained as part of a PPA, or the confidence to operate directly on the spot market. Finally, storage could also be useful if in the future wind farms are offered non-firm connections, i.e. if they are not entitled to receive constraint payments.

Storage can also prove useful for demand sources. Customers on time-of-use tariffs can reduce imports from the grid at times of high prices, as well as reduce network service charges, for instance through triad avoidance [30].

Finally networks may also benefit from storage through deferral of transmission or distribution reinforcement. This is particularly beneficial to distributed storage, in avoiding the significant cost of upgrading distribution networks to meet any future increases in peak demand [1]. However, transmission network operators in the EU are not allowed to own storage assets as they are currently classed as generators. This, together with further barriers to storage, is discussed in the next section.

*2.2. Current regulatory barriers to storage adoption*

Investment in storage faces many barriers because of current policy and regulation, which are comprehensively reviewed by Anuta et al. and Grünewald et al. [31,32].

*2.2.1. Undetermined asset classification*

Energy storage systems are multifunctional, and may act as generator, consumer or network asset at different points in time or simultaneously. Current regulation classifies storage based on its primary function [33], leading to issues with ownership. According to EU law [22], transmission network operators are forbidden from participating in the electricity markets, and hence would be unable to supplement their return on storage devices through competitive market participation (in addition to network support activities). Whether storage is classed as a generator or consumer also impacts on transmission and distribution use-of-system charges. If a consumer, then often consumers are subject to taxes to subsidise renewables [31]. A new asset class for storage could overcome these issues.

*2.2.2. Lack of standards and experience*

Other than pumped hydro, storage technologies are still largely developing, hence there is currently a lack of standards on their design, deployment and evaluation of their economic value [31]. For a network operator, investment in traditional network assets offers a low risk investment with guaranteed revenue streams. In contrast, the high capital costs of storage, uncertain future income streams and lack of storage precedents, result in high risk proposition [31]. Hence storage may not 'fit' into the business model of traditional transmission system operators, relying instead on competitive market participants. Furthermore, the benefits storage may offer to grid or centralised generator utilisation and corresponding cost and efficiency benefits are difficult to quantify, although this paper aims to make this more straightforward in future.

#### 2.2.3. No incentive to provide flexible generation

The fixed premia widely used to incentivise renewable generation do not reward dispatchable facilities [34] and are often accompanied by export guarantees [35]. Hence renewable generation often operates at the expense of conventional plant, increasing system-wide integration costs through displacing more energy than capacity, and decreasing asset utilisation. As these costs are socialised, there is a lack of transparency over the true costs of inflexible renewable generation. A two-tier tariff could incentivise owners of renewable energy plants to provide dispatchable energy, as is the case on some Greek islands [36].

#### 2.2.4. Renewable energy subsidies

Whilst storage may provide indirect benefits to renewables in terms of reduced curtailment and hence increased penetration, the electricity itself that is stored may or may not be sourced purely from renewables, if the storage device is connected directly to the grid. This creates difficulty in terms of subsidising storage as a renewable device. However Krajačić et al. propose that a guarantee of origin scheme could alleviate such issues [37]. Even so, under current rules, electricity from renewables that charges storage before entering the grid cannot receive subsidies [22]. Therefore, connecting a wind farm to a storage device would forfeit any renewable incentives.

#### 2.2.5. No incentive to maintain power quality

Power quality is likely to deteriorate as the penetration of renewable energy increases, particularly distributed solar PV or other domestic microgeneration [38]. However, currently there is no incentive to improve power quality and it is difficult to quantify [39].

### 2.3. Current market design barriers to storage adoption

#### 2.3.1. Reserve market

In liberalised electricity markets, the reserve market may provide a significant income stream for storage technologies [40,41]. According to Wasowicz et al., revenue increases between 6.2% and 19.2% could be obtained for storage operators in Germany if grid support was supplemented with reserve services [34]. However, the state of charge of some storage devices may not be precisely known (lithium ion batteries being a prime example), hindering its operation in the reserve markets [31].

#### 2.3.2. Lack of market liquidity

It is currently estimated that 5% of all trades in the UK market occur on the spot market [42]. The remainder are executed under opaque bilateral contracts, and often between a supplier and its generation arm. This leads to low liquidity in the spot market, increasing the entry barrier to small scale storage and new entrants, as is the case currently with distributed generation [43].

#### 2.3.3. Insufficient remuneration for ancillary services

According to Ferreira et al., remuneration for ancillary services within the EU are currently insufficient to make storage economically viable [44]. Storage is not rewarded for its higher accuracy, faster response and greater ramp rates in comparison to conventional ancillary service providers. In the US however, regulation changes in 2013 stipulate that improved performance is now valued [31]. Storage devices (particularly batteries and flywheels) can provide a better service than gas turbines and engines, meaning that the same level of service could theoretically be provided with fewer MW of capacity; however, there is as yet no financial premium available for this.

#### 2.3.4. Small scale storage

It is worth highlighting the importance of small scale distributed storage, particularly for distribution network operators (DNOs). This could help mitigate peaks caused by future electrification of heat and transport [45], and to increase the penetration of distributed generation that can be managed with existing infrastructure. Electrification is an essential part of national decarbonisation strategies across Europe, but will radically alter the profile of electricity demand. For example, a million heat pumps or electric vehicles are estimated to add 1.5 GW to peak demand in Britain and Germany [25]. The distribution cables that serve individual buildings were not designed to handle reverse power flows, where embedded solar panels and combined heat and power units export up to higher-voltage parts of the network [38]. As this 'last mile' of the network is mostly buried under streets, it will be prohibitively expensive to reinforce, and so operators are considering storage as a lower-cost route to balancing microgeneration.

Despite this, current policy development tends to focus on large scale storage [31]. Furthermore, regulation changes could enable DNOs to operate in an active manner, undertaking regional balancing services to better manage power quality and network utilisation [46,47]. Storage could then be used as a regulated asset.

### 2.4. The storage technologies

There are many excellent reviews of the storage technologies available [1,44,48,49], hence this section simply aims to summarise key points regarding use, and recent data on cost and efficiencies.

The technologies broadly fit into three categories: bulk storage which operates over timescales of several hours to weeks; load shifting (minutes to hours); and power quality (seconds to several minutes) [48]. At the extreme, the UK can store around 50 TWh of natural gas, capable of discharging over 11 weeks [50]. This highlights the potential scale at which hydrogen or synthetic natural gas could be stored, with the ability to operate over seasonal timescales. Pumped hydro storage (PHS) and compressed air energy storage (CAES) are the other bulk storage technologies, on the scale of GW and GWh. The UK hosts around 2.5 GW and 25 GWh of pumped hydro, split across four facilities.

Battery technologies show lower capacities, and discharge over shorter timescales between several minutes to several hours [48]. Conventional batteries (lead acid and lithium-ion) have higher costs per kWh stored as they require fixed reagents, rather than large natural features to store energy (lakes and caverns). Flow batteries could attain lower specific energy costs ($/kWh) as the reagent volume could be increased with a simple storage tank; however their current low volume of manufacture retains higher costs. The modular nature of batteries favours distributed storage; however the linear economies of scale mean that the cell cost per kW or kWh are similar when moving from residential to utility scale batteries, although the balance of plant costs can reduce dramatically. Finally, electrochemical capacitors (ECs) and

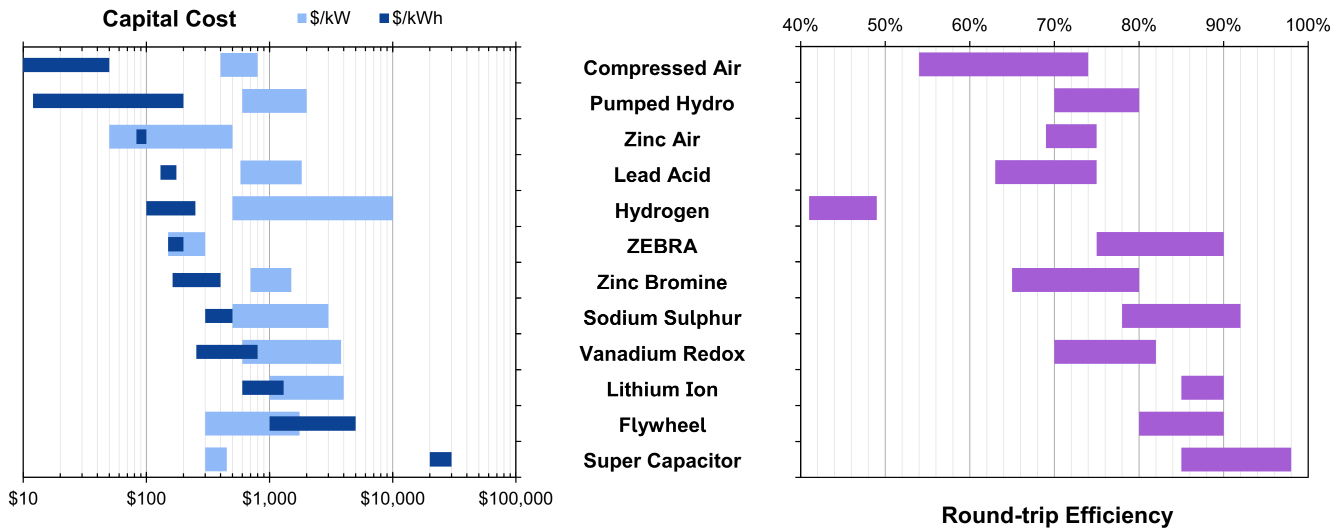


**Fig. 2.** Comparison of the specific cost in US dollars per MW and MWh for various storage technologies (left), and their system-level efficiency (right) based on [49,51,52].

flywheels display low energy to power ratios of less than 1, discharging in the seconds to minutes range [48].

The specific costs of the different technologies per kW and kWh are shown in Fig. 2 alongside their round-trip efficiencies, based on systematic reviews of hundreds of sources [49,51,52]. It is clear that there is significant divergence between the cost per unit power and unit energy. Bulk energy stores such as PHS and CAES tend to exhibit the lowest $/kWh, as they benefit from economies of scale in storage capacity, but also exhibit the lowest efficiencies. Conversely, electrochemical capacitors exhibit relatively low $/kW, but extremely high $/kWh of over $10,000/kWh.

This diversity in price and performance highlights the need for a range of market products to allow the different technologies to capture their true value. Bulk energy stores may find arbitrage a viable strategy, however electrochemical capacitors obviously require a market that can adequately reward its extremely fast response and ability to deliver high powers for very short times (for instance primary response).

### *2.5. Previous studies of optimal storage control*

Most previous studies that attempt to optimise the control of storage tend to perform global optimisation using mixed-integer linear programming, either to optimise for system-wide benefits or an independent investor. In addition, many previous works have looked only at arbitrage as a revenue source, assuming a price taker analysis [53,54]. Wasowicz et al. includes more applications, obtaining a multi-market optimisation but only under certainty [34]. In particular, they investigated the effect of grid congestion, storage technology and regulatory changes on the economic viability for an independent investor.

Sioshansi et al. investigated the impact large amounts of storage would have on the price spread and value of arbitrage by correlating historic prices to total system demand, and evaluating the extent to which storage would flatten peak demand and off-peak demand [55].

Connolly et al. tested practical control strategies for PHS, involving historical and future price forecasts of up to 24 h [56]. They found that on average, their practical strategy of optimising only 24 h ahead gained 97% of the truly optimal profits, however such a strategy requires good price prognoses. In addition, the model only looked at arbitrage, ignoring potential revenues from alternative markets (e.g. balancing, capacity). Similarly, Bathurst & Strbac relied on accurate forecasts of imbalance prices to investigate the integration of storage with wind, optimising the balance between reducing imbalance charges and gaining from arbitrage [57].

Therefore the aim of this project was to develop a simple algorithm that could optimise multiple revenue streams without the need for foresight. In particular, a simple method that could be run quickly and easily was desired, over a globally optimal solution. Hence the remainder of this paper sets out to explain the algorithm developed and subsequently the key findings.

## 3. Methods

The aim of this work was to design and demonstrate a simple algorithm to optimise storage operation for multiple revenue streams: arbitrage, reserve and coupling with a wind farm. We take a deterministic algorithm from Lund et al. [2] and Connolly et al. [56] that finds optimal operation for arbitrage, and add reserve and wind coupling, and demonstrate a selection of findings. The algorithm is technology neutral, and capable of simulating storage for power applications (e.g. batteries for arbitrage and reserve) and for bulk energy applications (e.g. hydro and compressed air for inter-seasonal storage).

Throughout this paper we compare three scenarios:

1. Arbitrage Only – 'ArbOnly'
2. Arbitrage with reserve, only taking availability payments – 'ArbAv'
3. Arbitrage with reserve, also taking utilisation payments – 'ArbAvUt'

The two reserve scenarios (ArbAv and ArbAvUt) are designed to explore the *minimum* and *expected* levels of income from providing reserve. ArbAv gives the lower bound: earning fixed availability payments for having the store available for reserve provision, but never receiving additional payments for actually providing reserve energy. This requires the store to maintain charge levels above a set limit and forgo earning revenue from arbitrage during availability windows. ArbAvUt provides a central estimate: earning the availability payments as above and additionally utilisation payments based on the historic need for reserve, which are typically much higher than earnings from arbitrage.

Analyses are carried out both under perfect foresight (PF) and no foresight (NF) of future market prices and reserve utilisations. Perfect foresight is useful to gauge the maximum value obtainable from a storage device, or if a sound future price prognosis is available. No foresight accepts that future prices and utilisation volumes remain unknown and optimises accordingly. In the case of ArbAvUt, the use of NF offers a practical tool, where the model could provide guidance on optimal operation based on live updates of utilisation levels (discussed further in Section 3.3). Nevertheless, in all scenarios, it is assumed the storage operator has access to wholesale market prices, that vary for each half hour settlement period.

The reserve scenarios are based on the 2013/14 STOR year, primarily because of good data availability for STOR in that year. Alternative balancing services (and previous STOR years) do not provide such granular data, and hence to avoid making many gross assumptions, the model is based on the STOR market. In reality, other ancillary services may tailor better towards storage's fast response times. Nevertheless, if better data became available, the model principles could be adapted to the details of other services.

### 3.1. An overview of the algorithms

Fig. 3 outlines the overall process the algorithm follows. If no reserve services are offered (i.e. ArbOnly), then arbitrage is optimised over all settlement periods and profits are calculated. If reserve services are offered (ArbAv and ArbAvUt), then it is assumed that no operation is permitted within availability windows unless called upon for reserve (as is the case with STOR). Reserve utilisation and availability services are then implemented within the availability windows and total profits calculated. The two options are discussed further below, with subroutines A to D detailed in the online supplement.

### 3.2. Arbitrage only (perfect foresight)

The EnergyPLAN algorithm for arbitrage described by Lund et al. [2] works by finding optimal charge-discharge pairs: the period with maximum price where discharging should occur, and a corresponding period with minimum price where recharging should occur. If the device can be fully utilised during these periods then they are removed from the series, and the next charge-discharge pair is found. Charge-discharge pairs are only accepted if they are profitable, accounting for the round trip efficiency of the storage device and other marginal costs. Low efficiency devices, or periods with homogenous prices will therefore see limited utilisation.

On the first iteration there are no constraints on which hours or how much capacity is accessible, and so these will be the maximum and minimum priced hours respectively. As the algorithm progresses, constraints on when recharging can occur become binding, so as not to exceed the maximum or minimum possible charge levels.

Lund shows that this arrives at the global optimum for profit [2], which we confirmed using a simple linear program written in GAMS. A simple example is presented in Fig. 4, and the online supplement gives a full mathematical description (subroutine A in Fig. 3).

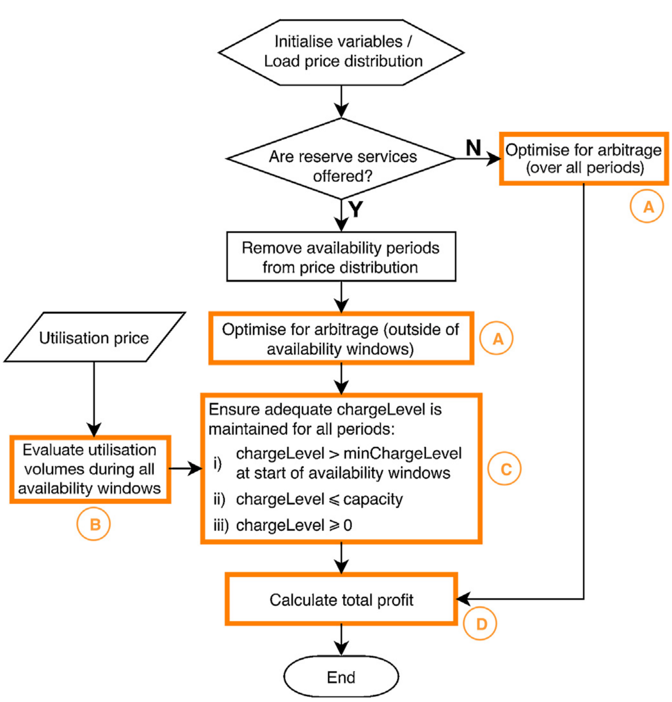


**Fig. 3.** An overview of the algorithm. Subroutines A to D are discussed in the online supplement.

### 3.3. Arbitrage + reserve (perfect foresight)

The extension of this algorithm to consider reserve consists of four parts:

- First, energy prices are removed during the windows where reserve is provided
- The device is then optimised for arbitrage outside of these windows
- Additional discharge due to reserve utilisation are added onto the profile
- Finally, the operation outside of availability windows is modified to recover any discharges due to reserve utilisation, and ensure that additional constraints are met.

The algorithm initially optimises for arbitrage in all periods *outside* of availability windows, as it is assumed the device is forbidden from providing arbitrage when committed to provide reserve. Reserve services are then introduced through a further step. Two scenarios representing extremes of income are considered: with no utilisation (ArbAv), and with typical utilisation (ArbAvUt). In both cases, identical remuneration for availability is received, however the later receives additional payments for energy discharged during availability windows, at the request of National Grid.

For the ArbAvUt scenario, the utilisation volumes are determined based on the input utilisation price and data for STOR utilisation provided by National Grid [14]. These volumes are then applied during availability windows. We take historic STOR utilisation from 2013/14 STOR year [58]. This gives the average daily profile for working and non-working days during each season, and the total volume for each day of the year. We combine these to form an estimated half-hourly profile of STOR demand, and interpolate the price offered for this utilisation from the supply curve (or 'price ladder') for that season [59].

For the ArbAv scenario, there is no utilisation hence no change in charge level during availability windows. For ArbAvUt, the charge level will decrease during some windows, meaning that additional recharging will be needed between windows. The algorithm then checks that three conditions are met:

1. Minimum charge level prior to every availability window
2. Charge level during all periods is less than or equal to maximum capacity
3. Charge level during all periods is greater than or equal to zero

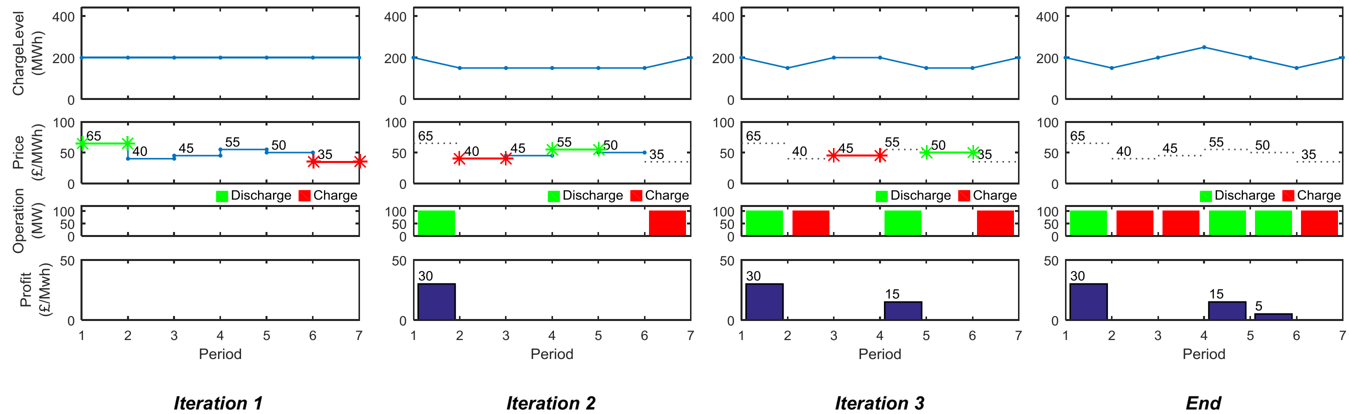


**Fig. 4.** A simple example of optimising for arbitrage over 6 settlement periods. Starting from the top, the plots show the charge level, spot price (with maxPeriod and minPeriod highlighted by stars), operation profile and profit. From left to right shows the advancing iterations. Note the diminishing profit for each charge/discharge pair, and removal of periods from the price series after each iteration (as the maximum charge/discharge capacity is utilised during those periods).

If any are not met, charging/discharging is altered during the most economical feasible periods to accommodate the conditions. Fig. 5 gives a graphical explanation of this process, and a mathematical description is provided in the online supplement (subroutines B and C in Fig. 3).

### 3.4. Introducing no foresight

Under perfect foresight, future market prices are known precisely, hence the storage can take advantage of fluctuations in the market price over periods of hours, days or even months for large capacity seasonal storage. This approach is only practical if a good price prognosis is available, or if used to evaluate the return on storage under future market price projections.

In reality, future prices and utilisation volumes are not known in advance, hence the algorithm's data inputs were modified to operate with no foresight. For the arbitrage-only scenario, a future price series was estimated based on the average daily price profile for each season in the previous year (see supplement Section 2.5 for more detail). The model was run with the estimated price series, and the resulting operation profile was combined with the real outturn prices to calculate the profits.

The ArbAv and ArbAvUt scenarios also use these estimated price series to optimise for arbitrage outside availability windows. To accommodate no foresight of future utilisation volumes, the algorithm was modified to form a stepwise process. Utilisation volumes for the first window are revealed, with any recharging to meet the next minimum level requirement, and any corrective

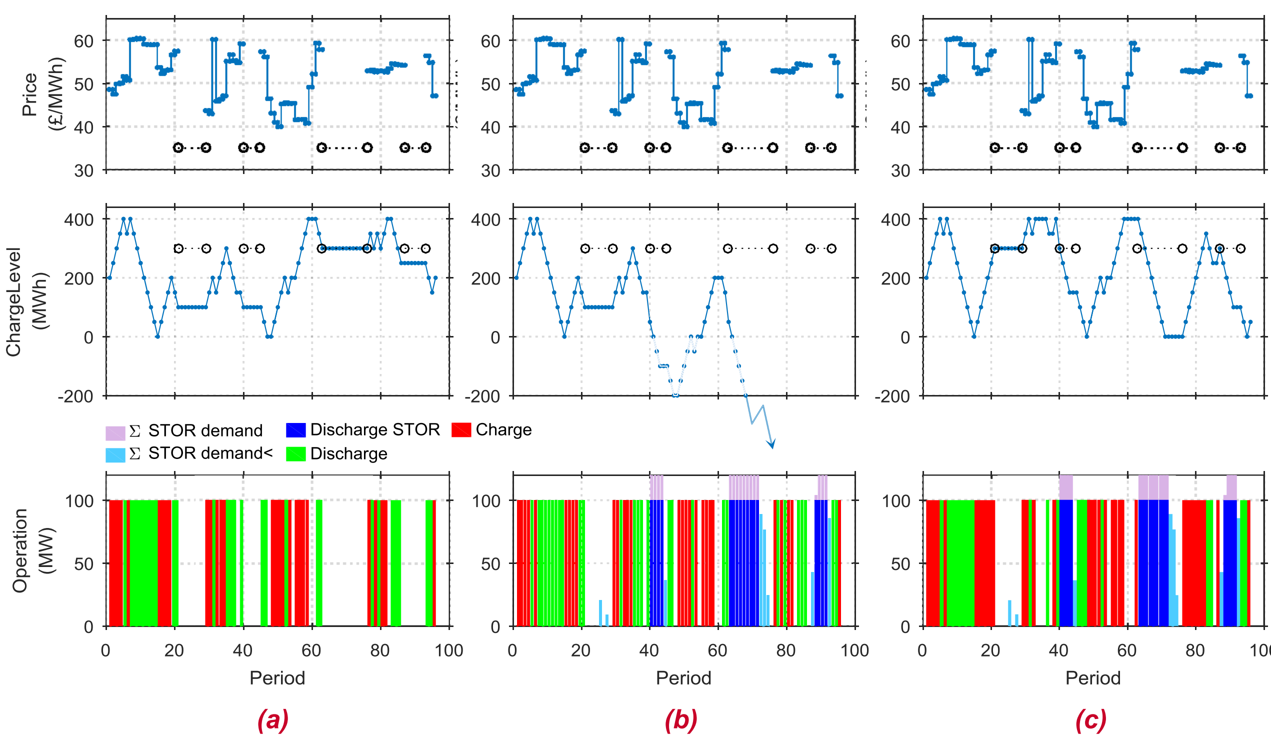


**Fig. 5.** Example operation with reserve under perfect foresight. Starting from the top, the plots show the charge level, price series (excluding availability windows) and operation profile over the settlement periods. The black circles denote availability windows, as well as the minimum charge level required at the start of availability windows (in this case 300 MWh). From left to right the panels show: (a) After optimising for arbitrage outside of availability windows. (b) After addition of utilisation volumes to operation profile – note the negative charge levels (that are corrected in the next step). (c) After ensuring charge level is maintained at satisfactory levels. This algorithm therefore assumes perfect foresight of both future prices and utilisation volumes, as ALL volumes are revealed before corrective action (c) is taken.

actions to retain the charge level between zero and full capacity, made *after* the first window (i.e. with hindsight of the utilisation volume) and *before* the next (i.e. with no foresight of future volumes). The process is then repeated for subsequent windows. In contrast, under perfect foresight there was no constraint on when these actions could take place, i.e. they could occur *any* time prior to or after the corresponding window. This method is further explained and visualised in the online supplement.

### 3.5. Application to a wind farm

The above methods were also applied in conjunction with a wind farm, to improve control over when the electricity is delivered. In effect, the wind farm is able to perform arbitrage, with the constraint that storage charging is limited to the output of the wind farm (assuming no import connection to the grid) – as in Fig. 6. Hence the scenario considered is arbitrage under perfect foresight. We use Whitelee wind farm as an example, taking its final physical notifications (FPN) of output during the 2013/14 season, retrieved from Elexon.

### 3.6. Financial calculations

Following the DOE/EPRI convention, the capital cost of battery systems was represented by the sum of a power ($/kW) and energy ($/kWh) term, to allow systems of different c-rates to be compared. We ignore economies of scale for battery production, and assume that the specific cost (per kW or kWh) is constant regardless of battery capacity.

For sodium sulphur (NaS) batteries, capital costs of 474 $/kW plus 372 $/kWh (at 80% depth of discharge) were assumed, together with operational costs of 4.5 $/kW/yr [60–62] and a currency conversion rate of 1.5 $/£. For example, a 3 MW, 30 MWh battery was assumed to cost:

$$\begin{aligned}\text{Capex} &= \frac{3000 \times 474\$/\text{kW} + 30,000\text{kWh} + 372\$/\text{kWh}}{3000\text{kW}} \\ &= 4194\$/\text{kW} \approx 2796£/\text{kW}\end{aligned} \tag{1}$$

In addition, an efficiency of 80% and cycle life of 5500 cycles (at 80% depth of discharge) was assumed [60,63,64]. Note that lifetime is defined as the number of cycles before a 20–30% drop in capacity is observed. Hence the battery may be able to continue running post this period, but with reduced storage capacity and potentially lower power outputs due to an increase in internal resistance [65]. These effects have not been accounted for in this analysis.

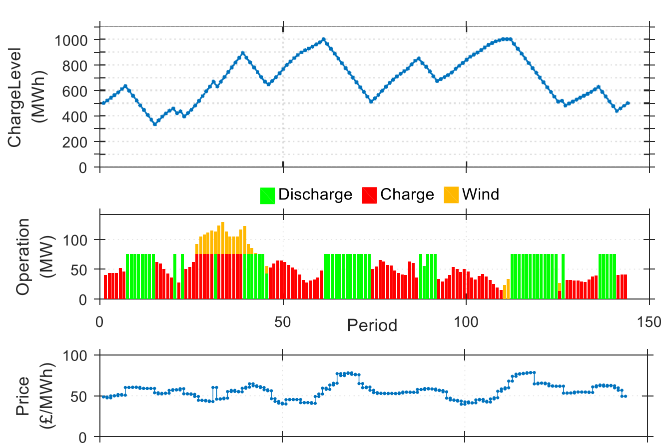


**Fig. 6.** Exemplar operation for a storage device in conjunction with a wind farm. Note how the charging is limited to the output of the wind, and some wind must be sold directly to the grid during times of high output.

For lithium ion (Li) batteries, capital costs of 1000 $/kW plus 700 $/kWh [66,67] were assumed, with operational costs of 9.2 $/kW/yr and an efficiency of 90% [60]. A lifetime of 6000 cycles was assumed [65]. For both technologies, costs of capital have been ignored. For both NaS and Li batteries we note that there is a broad range for system costs and lifetimes, and as these are rapidly evolving any choice of cost data will soon be obsolete. We choose a single, central value for each technology to perform the financial case study, and note that our primary metric (annual return on investment) scales inversely with capital cost. If, for example, capital costs fall by 50% from the values listed above, then annual returns will be double those presented in our results.

For each scenario, the profits of the relevant components are calculated using Eqs. (2)–(4). The components are then summed to form the total profit for each scenario.

$$\begin{aligned}\text{Profit}_{\text{arb}} = &\sum_{\substack{\text{All periods}\\ \text{outside windows}}} Q_{\text{out}} \times (P_{\text{util}} - MC_{\text{out}}) \times \eta_{\text{out}} \times TS \\ &- \sum_{\substack{\text{All periods}\\ \text{outside windows}}} \frac{a_p \times (P + MC_{\text{in}}) \times TS}{\eta_{\text{in}}}\end{aligned} \tag{2}$$

$$\text{Profit}_{\text{av}} = \sum_{\substack{\text{All periods}\\ \text{within windows}}} P_{\text{availability}} \times Q \tag{3}$$

$$\text{Profit}_{\text{ut}} = \sum_{\substack{\text{All periods}\\ \text{within windows}}} (Q_{\text{out}} \times P_{\text{util}} - MC_{\text{out}}) \times \eta_{\text{out}} \times TS \tag{4}$$

$Q_{in}$ and $Q_{out}$ are the input and output power capacity (charging and discharging in battery terminology; pumping and turbining in hydro terminology) [MW]. $\eta_{in}$ and $\eta_{out}$ are the charging and discharging efficiencies, which were set to be equal so that round-trip efficiency $\eta_{out}^2 = \eta_{in}^2 = MC_{in}$ and $MC_{out}$ are the marginal cost of charging and discharging [£/MWh], here taken as zero. $P$ is the spot price [£/MWh]. The factor of $TS$ (which here equals 0.5) is introduced to convert MW for each half hour settlement period to MWh. $P_{availability}$ the availability price [£/MW/hr], $P_{util}$ the utilisation price [£/MWh], and $Q$ is the installed capacity [MW].

This method of calculating profits means that any charging outside of availability windows is associated with the arbitrage component – including charging in preparation for STOR utilisation during a window. Devices can therefore register a financial loss from arbitrage when providing reserve utilisation.

The annual rate of return (ROR) for a device is based on its annual profit divided by the upfront capital cost (i.e. ignoring the time-value of money):

$$ROR = \frac{\text{Profit}[£/\text{kW/yr}] - \text{Opex}[£/\text{kW/yr}]}{\text{Capex}[£/\text{kW/yr}]} \tag{5}$$

## 4. Results and discussion

This section first explores the impact of various technology parameters (charge/discharge efficiencies, c-rates, and capacity) upon operating profile, profits and rates of return, all under perfect foresight. Some example applications are then demonstrated, calculating the rate of return for two battery technologies and its sensitivity to reserve utilisation and the introduction of no foresight. Lithium ion and sodium sulphur batteries are used as exemplary technologies, both being relatively well developed for stationary storage, and possessing different cost and technical characteristics. Finally the output of a wind farm is integrated, to observe the value that storage may provide to farm operators, by shifting delivery of electricity from periods of high wind output and low price, to periods of low wind output and high price.

All scenarios are based on historic half-hourly price data from the British electricity market, assessed over the period 01-04-2013 to 31-03-2014 unless otherwise stated.

### 4.1. The effect of efficiency

This section evaluates the effect of round trip efficiency on profits for our three scenarios under perfect foresight:

i Arbitrage only – 'ArbOnly'
ii Arbitrage with availability (but no utilisation) – 'ArbAv'
iii Arbitrage with availability and utilisation – 'ArbAvUt'

Assumptions include: c-rate of 0.1, STOR utilisation price of 89 £/MWh, availability price of 5 £/MWh (based on the 2013/14 average for STOR [58]) and no marginal costs of charging/discharging other than electricity purchased.

The total specific profit for each scenario at various efficiencies is shown in Fig. 7. At 100% efficiency, ArbOnly offers a specific profit (per kW of discharge capacity) of approximately 70 £/kW/yr, which lies between the values offered by scenarios ArbAv and ArbAvUt (the extreme cases of arbitrage with reserve). However for efficiencies below 72%, it is more profitable to offer reserve services even with no utilisation, than purely perform arbitrage. This is a result of the fixed payments for available capacity, which are independent of energy production and hence efficiency. This also leads the ArbAv scenario to plateau at even lower efficiencies. This is particularly pertinent for technologies such as compressed air and hydrogen storage, which exhibit round trip efficiencies in the range of 54–74% and 41–49 % respectively [49].

ArbAvUt offers the greatest specific profits, with smaller devices exhibiting higher values than larger devices. This is discussed further in Section 4.2. It is worth noting the significant reduction in profits in line with efficiency. A 3 MW/30 MWh device would gain 195 £/kW/yr if it were perfectly efficient, but only 113 £/kW/yr if it were 70% efficient.

A further breakdown into sub components of arbitrage – 'Arb', availability – 'Avail', and utilisation – 'Util' for each of the three scenarios is presented in Fig. 8 for a 100 MW/1000 MWh device.

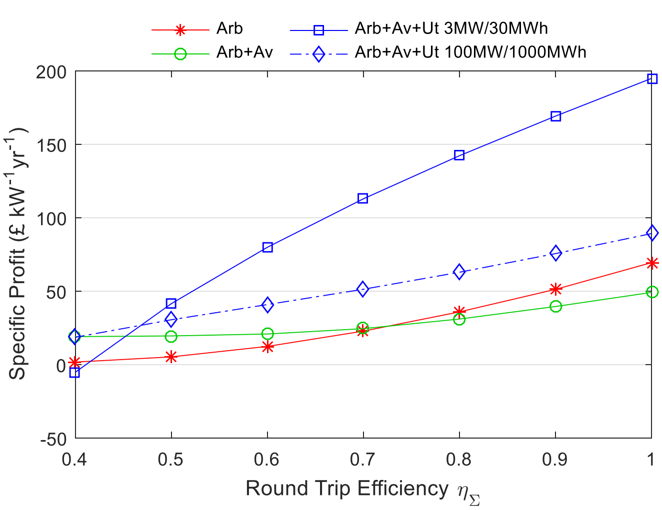


**Fig. 7.** The effect of round trip efficiency ($\eta_\Sigma$) on profits when operating in different markets. Note how arbitrage only becomes least profitable below $\eta_\Sigma = 0.75$. As discussed in Section 4.2, discharge capacity affects specific profits of the arbitrage + availability + utilisation scenario, so a 3 MW and 100 MW device are shown for comparison.

Also compared are operation profiles for round trip efficiencies of 70% and 100% over the first 4 days of the year.

There is stark difference between the operation profiles in Fig. 8a (top and bottom), highlighting the impact of low efficiency resulting in fewer periods where the price spread can make up for efficiency losses. This is further accentuated in the ArbAv scenario, comparing Fig. 8b (top and bottom). Many of the previous periods of high price are inaccessible for arbitrage due to overlap with availability windows; however, the availability payments make up for this. Finally for the first two days of the ArbAvUt scenario (Fig. 8c), no discharging occurs outside of availability windows, hence no positive profit is associated with arbitrage during this time. In fact, from Fig. 8, it is clear that the arbitrage profit component for this scenario is negative at all efficiencies. The arbitrage component consists of all charging/discharging outside of availability windows, which includes the profit generated from arbitrage, as well as the cost of charging to cover the utilisation during availability windows. Hence in the ArbAvUt scenario, as the charge efficiency drops the cost of charging in preparation for utilisation increases, resulting in an increasingly negative arb component.

### 4.2. The effect of discharge capacity

The *specific* profit is independent of discharge capacity for the ArbOnly and ArbAv scenarios. However it does affect the ArbAvUt scenario, via interaction with the volume of STOR utilisation that occurs. As STOR requires a generator to run at a fixed output level, smaller discharge capacities can be utilised more often (see Section 1.2 of the online supplement). A 10 MW device returns a specific profit of 180 £/kW/yr, whilst a 100 MW device returns 89.3 £/kW/yr, assuming a constant c-rate of 0.1, round trip efficiency of 1, STOR utilisation price of 89 £/MWh, availability price of 5 £/MWh and no marginal costs of charging/discharging.

As the discharge capacity reduces, the profit attributed to utilisation increases, in line with an increase in STOR utilisation (this equally causes a drop in the 'arb' component due to increased charging required outside of availability windows to cover the utilisation). In actual fact, the utilisation price was set to 89 £/MWh, which essentially places this device first in the 'merit order' for STOR despatch [59]. Thus the assumptions of the model mean that despatch occurs as long as national demand for STOR is greater than the device's discharge capacity.

Whilst the specific profit earned is greatest for smaller devices, the absolute profit increases with size. Fig. 9 highlights this, where the highest utilisation profit component is obtained for a 100 MW device. Above this, the increase in MW offered is outweighed by the reduction in the number of times the device is called upon, resulting in a net reduction in utilisation MWh. Naturally however, the availability and arbitrage components increase in an approximately linear fashion, resulting in an overall increase in total profits.

### 4.3. The rate of return attainable for arbitrage and availability

To place the specific profits discussed earlier into context, rates of return on exemplar sodium sulphur (NaS) and lithium ion (Li) batteries have been evaluated. The *specific profit* for the ArbOnly and ArbAv scenarios is dependent on the efficiency and c-rate, but is independent of discharge capacity (in contrast to the ArbAvUt scenario – discussed in Section 4.2). Fig. 10a and b present the variation of specific profit and rate of return with c-rate.

Li batteries achieve greater specific profits due to their efficiency advantage, but the lower cost of NaS batteries result in higher rates of return. Furthermore, the greatest specific profits (at low c-rates) do not result in the greatest rates of return, as the

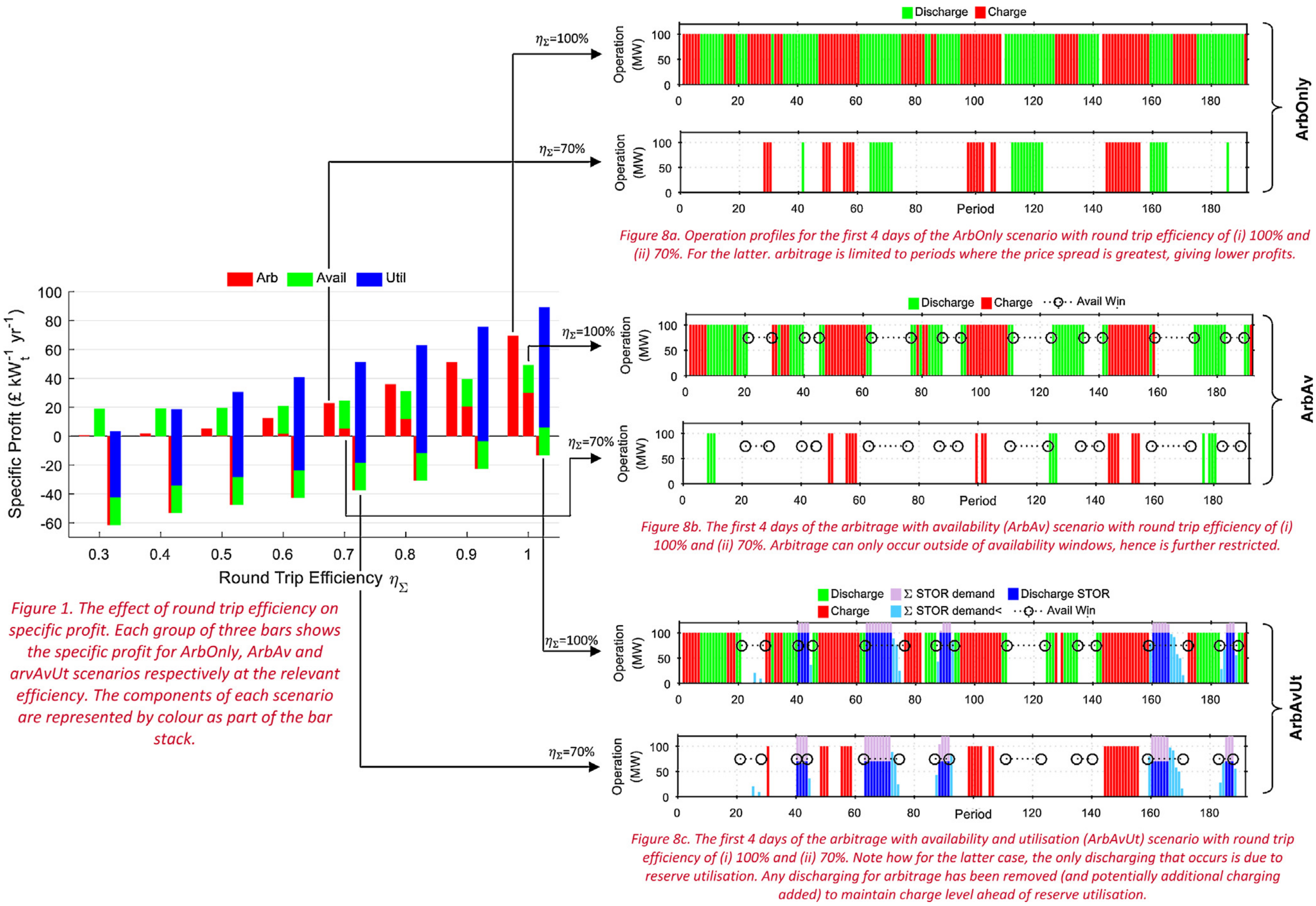


**Fig. 8.**

increase in capital cost outweighs the additional revenue captured. Nevertheless, a peak rate of return of only 1.98% is achieved, which is too low to be viable, as discussed in Section 4.4.

### 4.4. The rate of return attainable for arbitrage and reserve

Fig. 11 displays the rates of return and the specific profits obtained under the ArbAvUt scenario for NaS and Li batteries. Various storage capacities are displayed, with c-rates ranging 0.1–1 (discharge times of 10 h to 1 h).

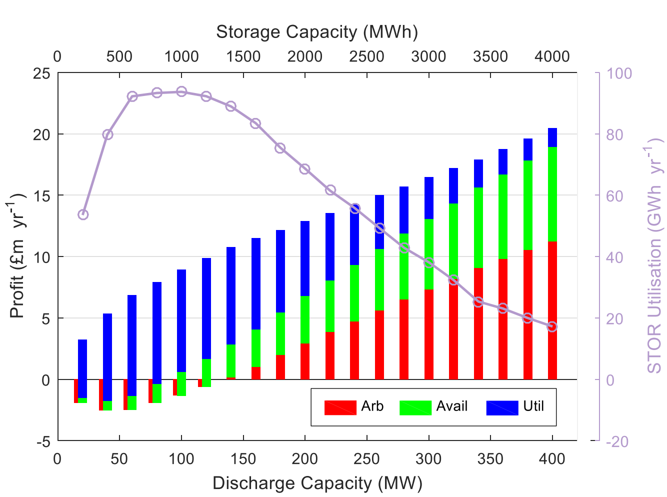


**Fig. 9.** The variation of total profit with discharge capacity with c-rate held constant at 0.1. Battery capacity was varied from 20 MW/200 MWh up to 400 MW/4000 MWh.

Devices with lower discharge capacities tend to exhibit greater specific profits (as discussed in Section 4.2). Moreover, devices with the lowest c-rates (longest discharge times), tend to offer the highest specific profits. This is due to the nature of the measure of specific profit, where inevitably devices with equal discharge capacities but larger energy stores are able to capture greater profits. However, the highest specific profits do not result in the highest rates of return (as can be observed comparing Fig. 11 (top and bottom)). For a given capacity, there appears an optimal c-rate to maximise rate of return. This behaviour is a result of the interaction between a reduction in specific profits as c-rates increase, but also a reduction in specific capital costs. For instance, a 3 MW/30 MWh sodium sulphur battery may achieve specific profits of 142.3 £/kW/yr, at a capital cost of 2796 £/kW (from Eq. (1)). However, a 12 MW/30 MWh NaS battery may achieve specific profits of 73.2 £/kW/yr (approximately half as much), but with capital costs of 936 £/kW (a third as much). Hence the latter gains a net benefit, returning 7.5% compared to 5.0% for the former.

When comparing the two battery types, the lower cost of NaS results in rates of return: up to 7.5%, compared to 4.4% for Li batteries. However, these values are too low to be viable. For the NaS battery, the assumed lifetime of 5500 full charge-discharge cycles is equivalent to 7.5 years under this scenario, which means the minimum rate of return to break even would be 13.3% due to depreciation. For the Li battery (with a life of 6000 cycles = 8 yrs), this minimum is 12.5%. These minimums ignore the cost of financing and the time value of money; with a 5% discount rate, the Li break-even rate would be 15.5%, with a 10% rate it would be 18.8%. However, the cycle life assumes end of life is when 80% of the original capacity remains. For grid storage, it may be worthwhile to

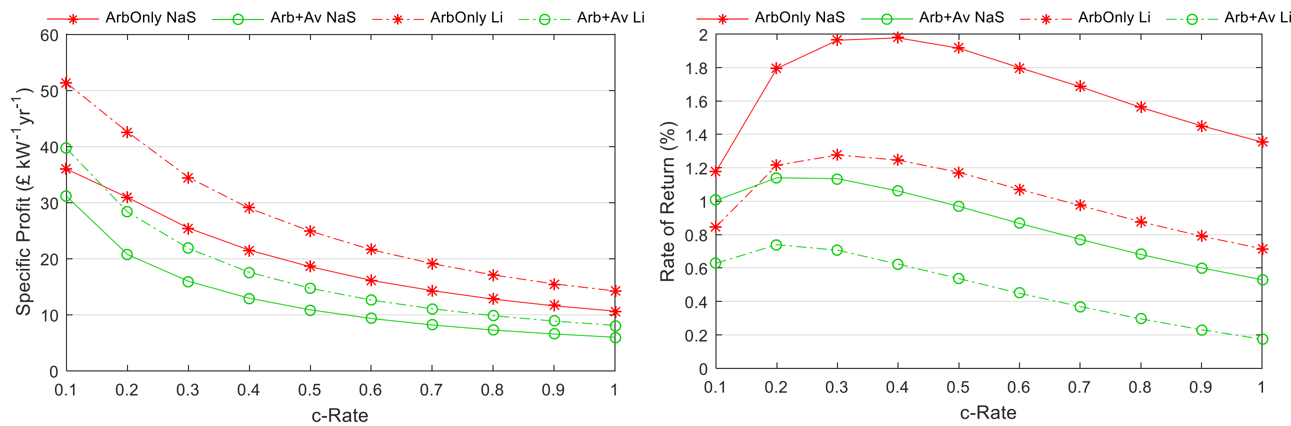


**Fig. 10.** Variation of specific profit (left), and the rate of return (right) with c-rate for the ArbOnly and ArbAv scenarios for sodium sulphur (NaS) and lithium ion (LI) batteries.

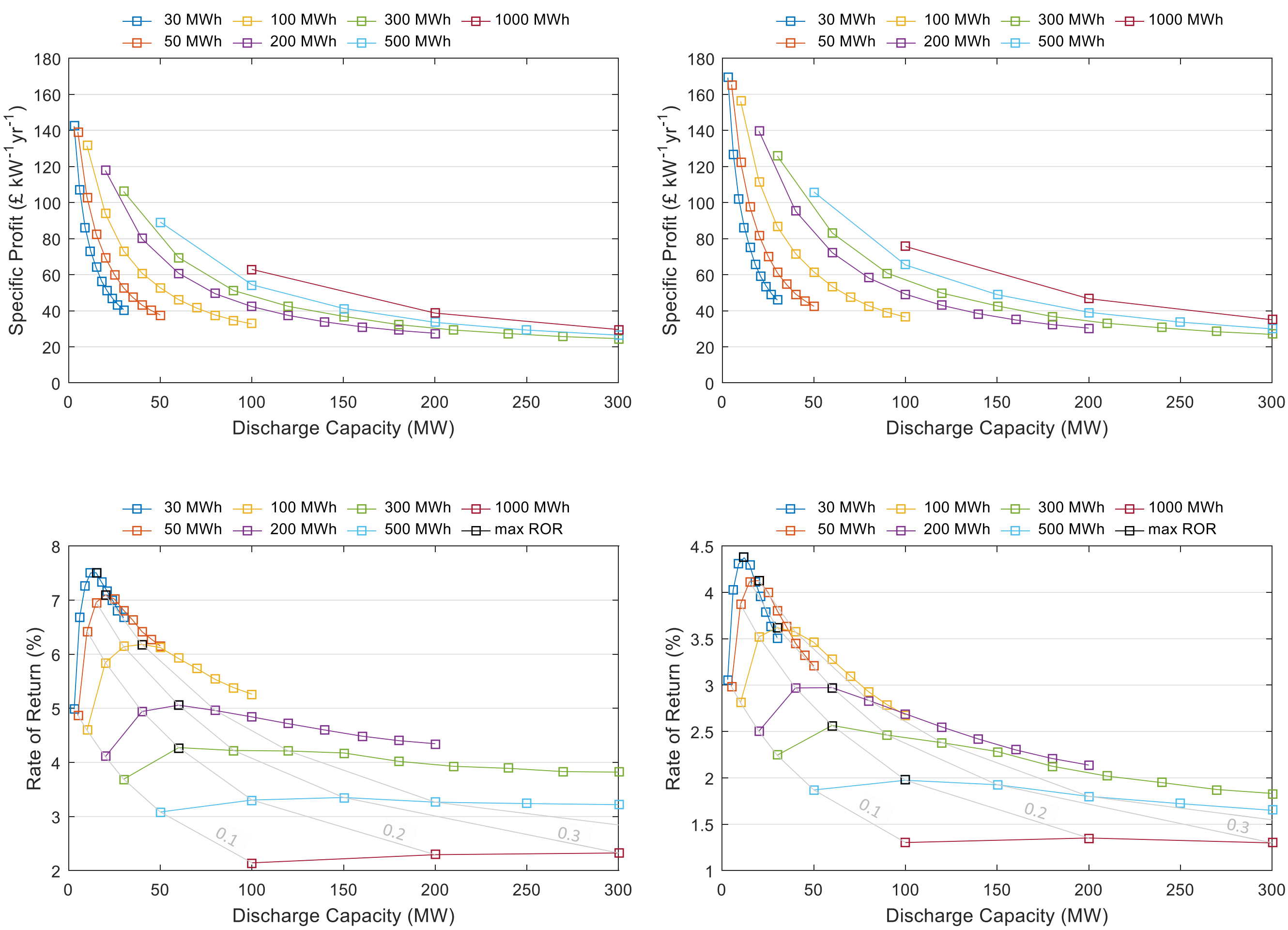


**Fig. 11.** Annual specific profits (top) and rates of return (ROR) (bottom) for the ArbAvUt scenario for a sodium sulphur (NaS – left) and lithiuim ion (Li – right) battery of various discharge and total capacities (MW and MWh). Lines of constant c-rate are shown for part of the figure to maintain clarity.

continue operation beyond this point. Despite this, some level of cost reduction, efficiency increase, or in particular increase in lifetimes would be necessary.

### 4.5. Sensitivity to assumptions for STOR utilisation

In order to test the sensitivity of the model to STOR utilisation volumes, randomness was introduced to the estimated national STOR demand profile by multiplying the hourly profile by a brown noise signal and rescaling to the original annual level of national STOR demand. The desired impact of introducing randomness was to change the timing of utilisation, and hence evaluate the impact upon the profits associated with the arbitrage component. However, whilst over a year the total volume of *national* demand is unchanged, the volume that is accessible to the storage device does change, due to the constraint that national demand must exceed the device's contacted output MW level. Hence the two effects are distinguished below.

The model was run 500 times with Monte Carlo inputs, which saw the total device utilisation volumes vary by 23.6% from minimum to maximum. The variation found in the total profit was 8%, of which only 1.4% was directly attributable to the different timings of utilisation, the balance a result of changing utilisation volumes. This variation is the result of shifting the time of utilisation, and hence the times (and by extension spot prices) when charging occurs in preparation of the availability windows.

By regressing the specific profit from each component against the utilisation volume across these trials, we find that the utilisation component displays a gradient of 89 £/MWh, i.e. the utilisation price (as the efficiency is 1 and $MC = 0$). The arbitrage component displays a gradient of −52.25 £/MWh, which is effectively the average cost of charging to replenish any utilisation during windows. The marginal profit earned as STOR utilisation increases is therefore 36.75 £/MWh.

### *4.6. Comparing perfect foresight with no foresight*

The previous sections have discussed the model under perfect foresight. This section explores the profits that can be gained where operating under no foresight. To reiterate the method, this implies the input price stream is an estimate based on past averages, and that STOR utilisation volumes are not known to the storage operator ahead of time.

For a round trip efficiency of 1, the profits with no foresight range between 88% (ArbOnly) and 98% (ArbAvUt) of those with perfect foresight. With an efficiency of 0.8, this drops to 75% for ArbOnly and 96% for ArbAvUt. The certainty of availability payments makes reserve more favourable with no foresight: the ArbAv scenario is more profitable than the ArbOnly scenario for efficiencies of less than 0.72 with perfect foresight; however for no foresight, this crossover point increases to 0.85. These observations can be explained by the two factors that no foresight introduces:

**The use of estimated future prices**, which affects the arbitrage component of all scenarios. This is due to the difference between the estimated and real prices. The ArbOnly scenario is most exposed as all profits are derived from arbitrage, whereas for the ArbAv and ArbAvUt scenarios, the proportion of profits from arbitrage are lower, due to the fixed availability and utilisation payments. Furthermore, the sensitivity of ArbOnly with no foresight to efficiency is likely due to the significantly fewer hours over which arbitrage operates at lower efficiencies (due to the higher price spreads required). Hence any discrepancies between the predicted and actual prices are magnified. At very low efficiencies, hardly any arbitrage is performed at all, resulting in the convergence of the profits for ArbOnly with perfect and no foresight.

**The unknown future STOR volumes**, which results in increased restrictions over when corrective action can take place. For instance, following utilisation in an availability window, the storage device may have to charge up prior to the next window, even if the price is high. Under perfect foresight, advanced planning is effectively permitted, such that the device could charge up ahead of both windows, avoiding the high prices in between.

A final point of note is that for the ArbOnly scenario, the algorithm with no foresight achieves 88% of the optimal profits, with an efficiency of 1. This can be considered quite high for having simply used a price profile based on averages over the previous year's STOR season. This is due to the importance of profile shape for arbitrage rather than mean value: it is safe to assume that on most days, discharging between 5–7pm would be optimal (due to likelihood of high prices *relative* to other times of day).

### *4.7. Integrating storage with wind*

Fig. 12a and b present results for integrating a storage device with the 322 MW Whitelee wind farm during 2013/14, considering arbitrage under perfect foresight. The figures display the rates of return for NaS and Li batteries with the same specifications as given in Section 4.3, of various capacities and c-rates. The returns are based on additional profits over and above selling the wind farm's output directly on the spot market.

Greatest returns were obtained for the smallest capacities, as the arbitrage benefits diminish as more storage is employed. The optimal c-rate is between 0.3 and 0.4 (3.3–2.5 h of storage capacity), implying that around 1 MW of battery capacity was optimal. Note that we ignore economies of scale in producing batteries, and so this result may change if larger batteries are significantly cheaper per MW.

The maximum rates of return of only 1.89% and 1.22% was recorded for NaS and Li batteries respectively, hence battery-based arbitrage with a wind farm is not viable with current battery costs and wholesale prices. Either further revenue streams must be sought, the capital cost of storage must dramatically fall, or the value of shifting the time of delivery must increase. The latter may occur in the future if wind penetration increases, and hence periods of high output depress the spot price more markedly.

Alternatively, integrating storage with a wind farm enables some level of control over the farm's output. This could provide

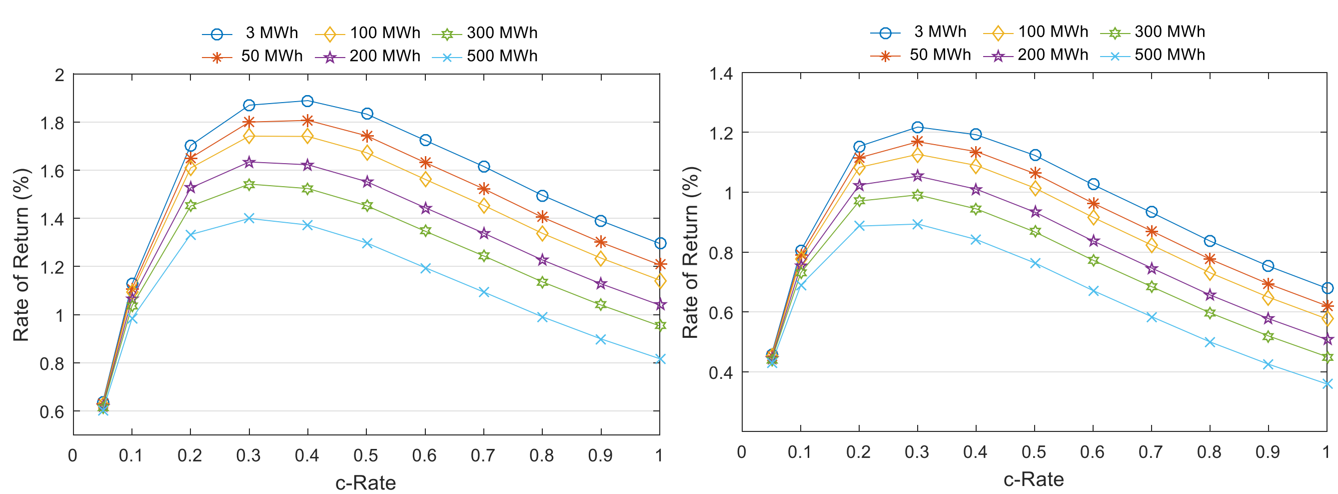


**Fig. 12.** The annual rate of return from arbitrage with a wind farm for storage capacities up to 500 MWh with various c-rates, considering a sodium sulphur (left) and lithium battery (right).

operators with enough confidence to sell output directly on the spot market as opposed to via a power purchase agreement (PPA). The fixed price per MWh offered in PPAs is lower than the average spot price of power as the counterparty is exposed to the risk of price volatility. If this risk premium is assumed to be 10% of the output-weighted average spot price, this would result in an additional income of 4,200,000 £/annum (£13,000 per MW of wind capacity), irrespective of storage size. It is not meaningful to add this to the rate of return of the storage device as this is a qualitative benefit, based on operator confidence in the marketplace. The size of storage has plays a qualitative role in reducing perceived investor risk.

## 5. Conclusions

As the penetration low carbon intermittent or inflexible forms of generation increase, system integration costs inevitably rise. Storage offers a solution to limit these costs, however to date it is still considered too costly to be an effective solution. Either costs have to decrease or storage operators have to maximise use of the devices to obtain as much profit as possible. Most studies in literature have aimed to optimise some form of storage either for a single revenue stream such as arbitrage, or performed analyses using computationally expensive global optimisation tools. Additionally, a good prognosis of future prices was typically required.

This research has developed and demonstrated a simple, generic algorithm that can optimise a storage device for arbitrage, with or without reserve services, under both perfect and no foresight. We make the Matlab implementation of this algorithm available to the community to help foster future research.

For an exemplar sodium sulphur battery, the maximum annual rate of return obtained for performing arbitrage only in the British market was 1.98%, but this increased to 7.50% for arbitrage with reserve, both under perfect foresight. For a lithium battery, returns were lower at 1.28% and 4.4%, due to the higher capital cost. Operation under no foresight was found to reduce profits by 5–25%. Also, integrating a sodium sulphur battery with a wind farm to shift time of delivery was found to produce a maximum rate of return of 1.89%, compared to 1.22% for a lithium battery.

With current battery lifetimes and electricity prices, the rates of return obtained even under perfect foresight are unlikely to prove viable. Either costs must reduce, alternative technologies with longer lifetimes (such as PHS) must be sought, additional revenue streams must become accessible, or the fundamental dynamics of the electricity market must change (e.g. daily price spread increasing due to increasing wind penetration).

Despite finding that storage would not be viable in any of the considered scenarios, the algorithm developed was successful at providing a simple means of optimising the control of storage, and future work should extend it to further revenues streams. In particular, the lack of transparent data resulted in the use of STOR market data for reserve services, however the technical properties of storage mean that it may gain greater benefit from operating in shorter timescale markets, such as fast reserve or response. Alternative income may also be gained from:

- Triad avoidance in order to minimise transmission use of system charges (or maximise payments in the case of distributed generation);
- Reduce imbalance costs for a wind farm;
- Participate in flexible reserve in conjunction with a wind farm (assuming good forecasts are available at the week ahead stage in case opt out is required).

The algorithm could also be further developed to include impacts on lifetime within the decision process. Currently lifetime is post-processed as a result rather than an optimisation variable. Furthermore, refinements to the no foresight algorithm could be made through improved forecasting of future prices using correlation with temperature forecasts.

## Acknowledgements

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.est.2016.08.010.

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