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Community energy storage: A case study in the UK using a linear programming method

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Abstract

In this paper, we investigate how energy storage can be used to increase the value of community energy schemes through cost reductions, infrastructure support, increased scheme membership, and reduced carbon emissions. A linear programming optimisation framework is developed to schedule the operation of behind-the-meter energy storage such that costs are minimised, while keeping peak demands within allowable limits. This is also extended to model generation-integrated energy storage systems, where the storage is located in the flow of energy from primary source (e.g. wind) to a usable form (e.g. electricity). To demonstrate the potential of energy storage within a real community energy scheme, we present a case study of a community hydro scheme in North Wales, considering both battery storage and a reservoir-based storage system. It is found that either system can be used to substantially increase the membership of the scheme while avoiding impacts on the electricity network, but that storage remains prohibitively expensive when used for self-consumption of renewables and arbitrage. We also investigate the impacts of energy storage on the community's carbon emissions, showing that storage operation appears to provide very little additional reduction in emissions when grid average emissions factors are used.

Keywords: Micro hydro; Battery storage; Scheduling; Linear programming

Highlights:

- Methodology for assessment of generation-integrated and non-generation-integrated energy storage systems is developed.
- Assessment covers economics, environment, and network constraints.
- An efficient method of scheduling behind-the-meter storage is designed.
- Storage alongside a community hydro scheme in North Wales is investigated.
- Storage on a scale of 1 kWh per household can increase scheme membership by >30%.

Nomenclature:

A_h	Amp-hour charge throughput in a battery cell
c	Carbon intensity of grid power
C	Cash flow
$\overline{C}$	Charge power capacity of the storage
$\overline{D}$	Discharge power capacity of the storage
$\overline{E}$	Maximum allowable energy in store
$\underline{E}$	Minimum allowable energy in store
g	Local generation
$\overline{G}$	Generator capacity
k	Time step index
l	Load
n	Percentage increase in load; Year of cash flow
p	Net demand
p^+	Grid import
p^-	Grid export
Q_{loss}	Percentage capacity loss in the battery
r	Discount rate
s	Number of time steps in foresight horizon
t	Life of investment opportunity
Δt	Duration of time step
T	Absolute temperature
u	Storage charge/discharge power
x	Energy in store
η_c	Storage charging efficiency
η_d	Storage discharging efficiency
$\boldsymbol{\lambda}$	Vector of import prices
$\boldsymbol{\pi}$	Vector of export prices
M	Maximum import capacity
σ	Storage self-discharge rate (hourly)
Φ	Carbon emissions

ADMD	After diversity maximum demand
CIC	Community interest company
CRC	Carbon Reduction Commitment
DOD	Depth of discharge
FIT	Feed-in Tariff
GIES	Generation-integrated energy storage
MPC	Model predictive control
NPV	Net present value
PPA	Power purchase agreement
TOU	Time-of-use (tariff)

1. Introduction

1.1. Motivation

Community energy generation schemes have several advantages over small-scale technologies owned by individual consumers. They can offer lower-cost renewable energy while avoiding the need for individuals to make large initial investments. They also allow consumers to make use of natural resources in the local area, strengthening communities by providing financial returns that can be used to fund socially beneficial projects. Compared to household scale technologies, community schemes can benefit from greater economies of scale, and in many markets can access better export terms. For example, by arranging a power purchase agreement (PPA) with a supplier, a community scheme can receive payments for export even if explicit support schemes (e.g. feed-in tariffs) are reduced or removed, as is the case in the UK [1]. Globally, there are many community energy generation schemes covering a wide range of technologies for generating heat and power. In the UK there are over 200 community electricity generation schemes with an estimated combined capacity of 249 MW [2].

While a great deal of research has been conducted into energy storage alongside community wind and solar schemes [3, 4], very little attention has been given to the role that energy storage could play in community hydro schemes. This is surprising as hydropower accounts for over half of the world's renewables power capacity [5], with a recent study finding that 82,891 small hydropower plants are operating or are under construction around the world, and identifying potential capacity for another 180,000 new plants [6]. Within the UK alone, community hydro schemes have been implemented at many locations, yet none have energy storage alongside them. It seems likely that more will be developed in the near future, as projects in Wales have become more attractive following the introduction of business rates relief [7]. There is an urgent need therefore to understand how energy storage can be usefully integrated with community-scale hydro schemes.

1.2. Storage concepts for community hydro systems

First introduced by Garvey *et al* [8], a *generation-integrated energy storage* (GIES) system is an energy generation system with energy storage included in the flow of energy from primary source to useful energy (i.e. electricity or heat). This can be contrasted with a non-GIES system (comprising generation and standalone storage), whereby the input to the energy storage system is electricity or heat. A comparison of non-GIES and GIES systems in shown in Fig. 1. In the non-GIES system, energy undergoes one or more transformations to become electricity and any energy passed through storage undergoes two further transformations and two moves. In the GIES system, all electrical energy extracted has undergone two transformations. Energy put through storage is moved twice but not transformed further. Energy movements incur some losses but these are normally much smaller than the losses due to transformation. Since GIES systems reduce the number of transformations associated with the storage of energy, they can have far lower energy losses than non-GIES systems when energy is passed through storage. Readers are directed to Garvey *et al* [8] for a more detailed description of GIES.

Natural hydro systems with reservoir storage are a good example of existing GIES systems, and such systems also already exist for concentrating solar power [9, 10] with concepts proposed for wind [11-15] and nuclear power [16, 17]. In the case of a community hydropower system, the storage in a GIES system would most likely be a dammed reservoir upstream of the hydro generator, whereas a non-GIES hydropower system might have a battery behind the same meter as the hydro generator and the load (i.e. the households and businesses in the community energy scheme).

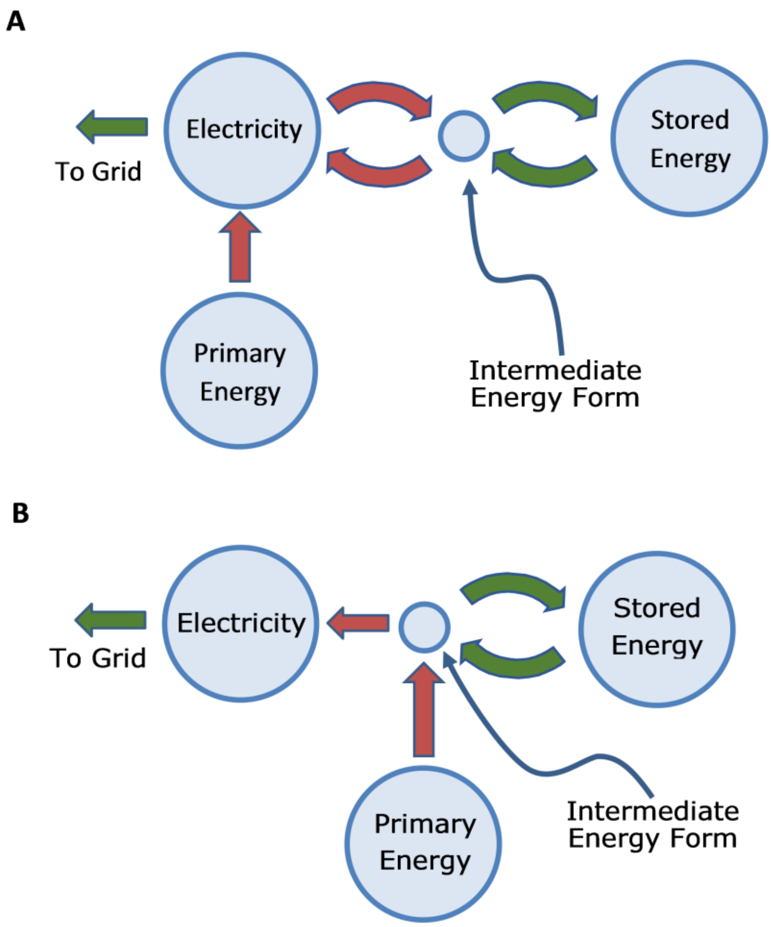

Fig. 1 Generation systems with storage: (A) Non-GIES system with storage and (B) GIES system. Red arrows represent *energy transformations*. Green arrows represent *energy movements* [8].

1.3. Objectives of the present work

A key factor in deciding whether to integrate any storage system is the value of the benefits provided compared to the cost of installing the equipment. While the latter is relatively easy to evaluate, the former is much more challenging. This paper addresses, therefore, the question: "*What is the value of generation-integrated and non-generation-integrated energy storage in community electricity generation schemes?"* with an emphasis on hydro schemes.

We present an efficient, general approach to scheduling the operation of behind-the-meter energy storage systems, based on the principles of model predictive control and linear programming. We use this approach to investigate the value of installing energy storage alongside a community hydro scheme, considering both a conventional non-generation-integrated energy storage system, taking the form of batteries, and a GIES system, taking the form of a reservoir. The value streams considered cover economics, the environment, and the impacts on the electricity network.

The specific contributions of this paper are:

- Introducing an efficient, general method for scheduling the operation of energy storage systems, accounting for cycling-induced battery degradation, differing import and export prices (for behind-the-meter storage units), network constraints, and feed-in tariff scheme requirements, as well as allowing limited foresight of generation and demand.
- Further developing the method to support the scheduling of generation-integrated energy storage systems.
- Using the method for a cost-benefit analysis of energy storage alongside a community hydro scheme, considering the needs of several stakeholders including members of the scheme, investors, and network operators.
- Comparing generation-integrated energy storage systems with non-generation-integrated energy storage systems in a community generation context.

1.4. Key features of our approach

Numerous approaches have been taken to optimising the operating schedule of energy storage systems. These include algorithmic approaches [18, 19], convex optimisation [20, 21], quadratic programming [22, 23], mixed integer linear programming [24-27], and linear programming [28, 29]. Of these, linear programming approaches have the advantage of being efficient while also being widely applicable. However, the nonlinearities associated with the degradation of electrochemical electricity storage technologies have previously been problematic. The method presented here avoids these problems by combining a cycling-induced degradation model for a promising Li-ion battery storage technology with a model predictive control-based linear programming approach to storage scheduling.

The application of our method focuses on large community storage systems connected to a shared generator, rather than in-home storage systems. This decision is partly due to the benefits offered by larger systems over in-home systems, and partly because accurate analysis of in-home storage systems must account for different levels of storage deployment by each member of the scheme. Depending upon how local generation output is allocated to individual scheme members, independent decisions taken by individuals could affect the investment value of storage. This would be a small-scale example of storage being part of the price formation process and “cannibalising” its own market [30-32]. Such analysis is beyond the scope of this work.

In assessing the techno-economics of adding storage, we assume that the single large storage system would be installed and operated by the operators of a community energy scheme (e.g. a community interest company, or CIC), and funded by investors in the scheme. Any techno-economic benefits arising from the added storage would be returned to the investors in the form of an improved financial performance.

2. Methodology

In this section, the methods used are set out, covering storage scheduling, battery degradation, generation-integrated energy storage systems, and the quantification of carbon emissions.

2.1. Storage scheduling

We now present an optimisation framework for energy storage scheduling, based on linear programming and model predictive control (MPC) for computational efficiency. While developed for the study reported here, its general nature means it could be used to model the operation of energy storage in various other scenarios (e.g. in an individual household, or for modelling the operation of thermal energy storage systems).

The storage operating schedule, and hence total electricity cost for community members, is found over the course of the analysis period (e.g. one year) using an MPC approach. In the MPC approach, the optimal storage schedule is found over a *foresight horizon*, over which there is perfect foresight of the community’s electricity demands, local generation, and prices, at half-hour resolution. The operating schedule is then followed until the foresight horizon can be updated. Here we use a foresight horizon of 96 hours and an update period of 24 hours. This means that the optimisation is carried out over hours 1-96, then the optimal operating schedule for hours 1-24 is used, then the optimisation is carried out over hours 25-120, then the optimal operating schedule for hours 25-48 is used, and so on, until the storage operating schedule has been developed for the whole analysis period. In the first MPC iteration, we set the storage to be full; the reason for this is explained later in this subsection. In the following MPC iterations the initial store charge in the optimisation problem is set to the actual one at the end of the most recent update period.

Since the storage control is based on an optimisation, the results shown here provide an upper limit on the potential for storage as if the controller had perfect foresight of demand, generation, and price. In reality, demands and generation cannot be predicted perfectly, though techniques for forecasting renewable resources and electricity demands are continually developing. It should be noted that the analysis is performed here with only one year’s worth of data, as explained later in Section 3.1, and it is possible that this happened to be a poor year for generating savings using storage. Future work could apply this analysis to larger datasets if they become available, to gain more reliable insight into the savings achievable from deploying storage in community energy schemes.

In the following description of the storage scheduling algorithm, column vectors are denoted using bold characters. Inequalities involving vectors should be understood component-wise.

The foresight horizon comprises s time steps, indexed by $k \in \{1, \dots, s\}$. Each time step is Δt hours long. In the analysis presented in this paper, we use a 96-hour foresight horizon and data at half-hour resolution, hence $\Delta t = 0.5$ and $s = 192$. In this work we also assume that the foresight horizon always starts at midnight.

At time step k, the power balance for a consumer's net demand $p(k)$ is given by

$$p(k) = l(k) - g(k) + u(k), \tag{1}$$

where $l(k)$ is the community's load, $g(k)$ is the community's local generation, and $u(k)$ is the power flowing to/from an energy storage system, where power flows to the storage (i.e. charge) are positive, and power flows from the storage (i.e. discharge) are negative. Note that we are assuming that there is no curtailment of local generation. All powers are in units of kW.

To allow charge and discharge efficiencies to be taken into account, separate vectors for charge and discharge powers are used ($\boldsymbol{c}$ and $\boldsymbol{d}$ respectively), such that

$$u(k) = c(k) - d(k) \tag{2}$$

where $c(k), d(k) \geq 0$. As will become clear later in this section, the optimisation problem is set up in such a way that at each time step k, at least one of the optimal values of $c(k)$ and $d(k)$ will be equal to zero.

To calculate the cost of purchasing electricity from the grid, as well as the payments for export onto the grid, the s-length vector of net demands, $\boldsymbol{p}$, is decomposed as

$$p(k) = p^+(k) - p^-(k), \tag{3}$$

where $\boldsymbol{p}^+$ is an s-length vector of net import powers and $\boldsymbol{p}^-$ is the vector of net export powers.

The objective function is thus given by

$$\min \Delta t \boldsymbol{\lambda}^T \boldsymbol{p}^+ - \Delta t \boldsymbol{\pi}^T \boldsymbol{p}^- + 10^{-6} \|\boldsymbol{u}\|_1 \tag{4}$$

subject to

$$x(k) = x(k-1)(1 - \sigma \Delta t) + c(k)\Delta t \eta_c - d(k)\Delta t / \eta_d,\ k = 2, \dots, s \tag{5}$$

$$\underline{E} \leq \boldsymbol{x} \leq \overline{E}(100 - Q_{loss})/100 \tag{6}$$

$$x(s) = 0.5\big(\overline{E}\,(100 - Q_{loss})/100 + \underline{E}\big) \tag{7}$$

$$0 \leq \boldsymbol{c} \leq \overline{C} \tag{8}$$

$$0 \leq \boldsymbol{d} \leq \overline{D} \tag{9}$$

$$\boldsymbol{u} = \boldsymbol{c} - \boldsymbol{d} \tag{10}$$

$$\boldsymbol{p}^+ \geq \boldsymbol{l} - \boldsymbol{g} + \boldsymbol{u} \tag{11}$$

$$\boldsymbol{p}^+,\ \boldsymbol{p}^- \geq 0 \tag{12}$$

$$\boldsymbol{p}^+ - \boldsymbol{p}^- = \boldsymbol{l} - \boldsymbol{g} + \boldsymbol{u} \tag{13}$$

$$\boldsymbol{p}^+ \leq M \tag{14}$$

The set of electricity prices paid by the community for grid import over the foresight horizon is given by the s-length column vector $\boldsymbol{\lambda}$, and the set of prices paid to the community for export to the grid over the foresight horizon is given by the s-length column vector $\boldsymbol{\pi}$. For a unique solution, it is necessary that $\boldsymbol{\lambda} > \boldsymbol{\pi} \geq 0$. We disregard running costs in this analysis, as the costs of running a community energy scheme are unlikely to be strongly affected by the presence of an energy storage system.

The final component of the objective function, $10^{-6}\|\boldsymbol{u}\|_1$, is a penalty term that is included to ensure that the storage isn't needlessly cycled without benefit to the community. It represents the net present value of the whole-life costs of store deterioration due to charge/discharge in the present foresight horizon. As previously explained, $\boldsymbol{u} = \boldsymbol{c} - \boldsymbol{d}$, and the L1 norm of the storage operation is calculated using a linear formula $\|\boldsymbol{u}\|_1 = \sum_{k=1}^{s}\big(c(k) + d(k)\big)$.

Taking account of storage charge and discharge efficiencies of η_c and η_d respectively, and hourly self-discharge rate σ (where $0 \leq \sigma, \eta_c, \eta_d \leq 1$), the energy in store at the end of time step k is given by equation 5. Vector $\boldsymbol{x}$ is uniquely specified by $\boldsymbol{c}$, $\boldsymbol{d}$, and $x(0)$ (the energy in store at the start of the foresight horizon).

The constraints on $\boldsymbol{x}$ in equation 6 are the storage's energy constraints (where $\underline{E}$ and $\overline{E}$ are the storage's minimum and maximum allowable energy levels, respectively), and the constraints on $\boldsymbol{c}$ and $\boldsymbol{d}$ in equations 8 and 9 are the storage's power constraints (with $\overline{C}$ and $\overline{D}$ being the charge power capacity and discharge power capacity, respectively).

The constraints on $\boldsymbol{p}^+$ and $\boldsymbol{p}^-$ in equations 11 to 13 ensure that the optimal values correctly represent the net import and export powers. Equations 11 and 12 ensure that, at each time step k, $p^+(k)$ is greater than or equal to the maximum of 0 and $p(k)$ (calculated as $l(k) - g(k) + u(k)$, as defined by equation 1). Combined with equation 13 to calculate $p^-(k)$ (which effectively combines equations 1 and 3), the objective function will ensure that the optimal value of $p^+(k)$ is equal to the maximum of 0 and $p(k)$ (since having $p^+(k)$ any greater than necessary will increase the value of the objective function, which the optimisation is seeking to minimise) and that the optimal value of $p^-(k)$ is equal to the maximum of 0 and $-p(k)$. Note that this is only true if all export prices are lower than the import prices, i.e. $\boldsymbol{\pi} < \boldsymbol{\lambda}$, as is the case here. The L1 norm of u in the objective function will also ensure that at least one of $c(k)$ and $d(k)$ will be equal to zero.

The equality constraint of equation 7 is a terminal constraint ensuring that the state of charge at the end of the foresight horizon is equal to 50% of the remaining available storage capacity. This gives the storage equal opportunity to charge or discharge in future time periods. It should be noted that this constraint does not fix the state of charge to be 50% every midnight, since the 96-hour foresight horizon is updated every 24 hours.

In one part of this paper, it is supposed that the number of households in a community energy scheme is increased while the electricity grid connection is unchanged. Equation 14 is used to ensure that the maximum grid import power remains less than the maximum import capacity of the network, M. Assuming there is sufficient storage capacity, the optimisation procedure schedules the storage in such a way that grid import does not exceed M. If the storage cannot be operated to maintain grid import below M then the optimisation procedure fails. Where the grid import constraint is included, we set M as the maximum difference between the original load of the community (i.e. before the load is scaled up to represent the addition of households to the community) and the community's local generation over the whole duration of the study. In this way, storage can allow the community size to be increased with no impact on the electricity network. If necessary, a maximum export capacity could easily be added using a similar constraint on $\boldsymbol{p}^-$.

The optimisation problem is linear, and hence can be efficiently solved using dedicated linear programming solvers. Optimisation of the storage operating schedule over the foresight horizon is conducted using CPLEX (version 12.8). The MPC approach is run until the storage operating schedule has been developed for the whole analysis period or until the grid constraint cannot be met, indicating that the load is so high that the storage cannot keep the maximum grid import below M. As explained near the start of this subsection, in the first MPC iteration we set the storage to be full, i.e. we put $x(0) = \overline{E}$. This ensures that demand peaks that occur early in the analysis period can be dealt with.

We use equal time steps of 0.5 hours in this work. Unequal time steps could be implemented through modification of the objective function and constraints. An example application of this would be if one minute resolution data were available, and/or to account for the reduced accuracy of longer-term forecasting. Since there are 1,440 minutes in a day, it could take some time to develop the storage operating schedule over the analysis period if a multiple-day foresight horizon is being used, and in any case, it is highly unlikely that forecasting of load and generation could be achieved at one minute resolution for many hours hence. Therefore in those circumstances it might be desirable to use the first 30 minutes of data at one minute resolution, then to convert the remaining data in the foresight horizon to a lower resolution (e.g. 30 minutes).

2.2. Generation-integrated energy storage

In the next section, we examine the benefits of installing energy storage at a community hydro scheme, and compare the benefits of a battery system (i.e. a non-generation integrated energy storage system) with a reservoir just upstream of the hydro generator, which can only be charged using water flowing down the mountainside that would otherwise have passed through the hydro generator (i.e. a generation-integrated energy storage, or GIES, system).

To model a GIES system, where the only power conversion machinery is the on-site generator (e.g. the hydro generator in the case of the community hydro scheme studied in this paper), we must add two additional constraints to the optimisation problem laid out in section 2.1.

$$\boldsymbol{u} \leq \boldsymbol{g} \tag{15}$$

$$\boldsymbol{g} - \boldsymbol{u} \leq \overline{G} \tag{16}$$

where $\overline{G}$ is the capacity of the generator. In this case, $\boldsymbol{g}$ is the potential generation from the current water flow, and $\boldsymbol{u}$ is the withheld generation, i.e. water accumulating in the reservoir.

The first of these two additional constraints ensures that the storage is never charged at a higher rate than would otherwise be generated at the on-site generator, since in the case considered here, the energy for charging a GIES system can only come from the primary energy flow (e.g. the flow of water down the mountainside). The first constraint ensures that the storage is never charged from the grid, and hence could also be used to model systems that claim metered export Feed-in Tariff (FIT) payments, the regulations for which require a metering arrangement or disconnection relay to ensure that the storage is only ever charged using the FIT-eligible generation [33]. The second of the additional constraints ensures that discharge of the storage system never causes the generator's power capacity to be exceeded.

In the following section, when analysing reservoir storage alongside a hydro generator, we assume that the reservoir can potentially be charged and discharged at any rate up to the capacity of the generator (since a valve is likely to have little effect on the flow of energy out of a reservoir), so we set $\overline{C} = \overline{D} = \overline{G}$.

2.3. Battery degradation

When considering battery storage, we assume that a graphite-$LiFePO_4$ battery is used, and account for cycling-induced degradation of battery storage. The graphite-$LiFePO_4$ (lithium iron phosphate) based lithium-ion battery chemistry is one of the most promising for large-scale applications, due to its chemical and thermal stability and low cost. For a 2 Ah $LiFePO_4$ battery cell cycled at a C/2 rate, cycling-induced capacity fade is shown in ref. [34] to be given by

$$Q_{\text{loss}} = 30{,}330\exp\left(\frac{-31{,}500}{8.314T}\right)A_h^{0.552} \tag{17}$$

where Q_{loss} is the percentage capacity loss, T is the absolute temperature, and A_h is the cell's charge throughput in amp-hours, given in ref. [34] as $A_h = \text{cycle\_number} \times \text{DOD} \times 2$ (since equation 17 is valid for 2 Ah cells, as stated above). DOD is depth of discharge. We assume an operating temperature of 15 °C, slightly higher than the mean atmospheric temperature in the UK, and a depth of discharge of 100%. It has been shown that at low C rates, DOD has a negligible effect on the cycle-life of a $LiFePO_4$ battery [34]. Fig. 2 shows the capacity loss against number of cycles as predicted using equation 17; evidently temperature has a strong influence on cycle-life, and the UK climate is reasonably well-suited to electrochemical storage in this respect.

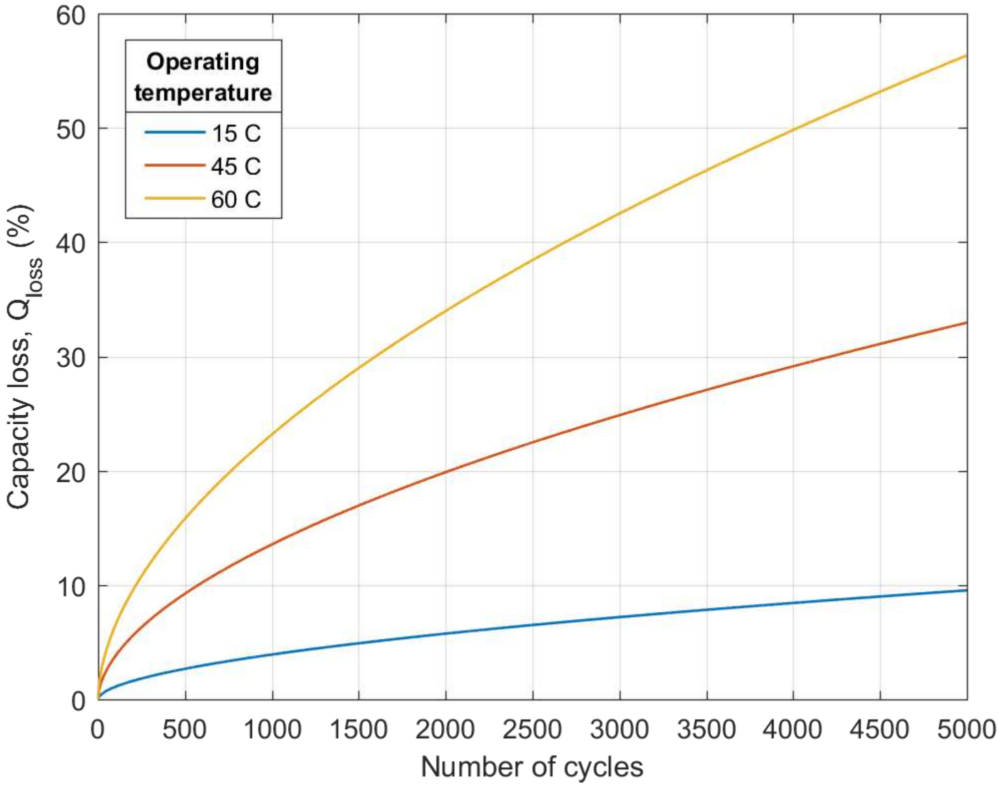

Fig. 2 Capacity loss against number of cycles for a $LiFePO_4$ battery, as calculated using the cycle-life model [34].

Our calculations begin by taking the charge throughput to be zero at the start of the analysis period (i.e. at the start of the first foresight horizon), then use equation 17 to update the remaining storage capacity at the start of each subsequent foresight horizon.

2.4. Economics and emissions

To determine the economic value of investment in community energy storage systems, we use the concepts of net present value (NPV) and breakeven cost. The NPV of an investment is given by

$$\mathrm{NPV} = \sum_{n=0}^{t} \frac{C_n}{(1+r)^n} \tag{18}$$

where C_n is the cash receivable after n years, r is the discount rate, and t is the life of the opportunity in years [35].

The breakeven cost is defined here as the capital cost of the storage system (i.e. cost in year 0) for which $\mathrm{NPV} = 0$, and is given by

$$\mathrm{BEC} = \sum_{n=1}^{t} \frac{C_n}{(1+r)^n} \tag{19}$$

If the storage system has a capital cost lower than the breakeven cost then the investment will have a positive NPV.

Environmental aspects of energy generation are playing an increasingly important role. We remark that the optimisation methodology of this paper can be adapted to either optimise a trade-off between costs and greenhouse gas emissions or minimise the latter with a disregard for economic costs. However, in this paper, we study the greenhouse gas emissions associated with storage operating schedules based on cost minimisation.

To quantify the emissions caused by the community's electricity consumption, we multiply the community's total grid import by the emissions factor used in the CRC Energy Efficiency Scheme for grid electricity in 2017-18, approximately 380 gCO_2/kWh [36]. In future work it is anticipated that we will make use of time-resolved carbon intensity data that has recently become available via the Carbon Intensity API developed by National Grid [37]. However the data currently provided through this service does not precede May 2018, and hence is not usable in the current work. Nevertheless, we have developed our methodology with this extension in mind.

If historical carbon intensity data were available at half-hour resolution, then multiplying it by the community's grid import over the analysis period would yield the total carbon emissions associated with the community's electricity consumption, given by

$$\Phi = \boldsymbol{c}^T \boldsymbol{p}^+ \Delta t \tag{20}$$

where $\boldsymbol{c}$ is a column vector of regional carbon intensity of generation (in gCO_2/kWh) over the analysis period and $\boldsymbol{p}^+$ is the column vector of the community's import over the same period. In the current analysis of course, every element of $\boldsymbol{c}$ is set to 380 gCO_2/kWh.

3. Case study on a community hydro scheme

3.1. Bethesda Energy Local Club

Using the tools developed above, we now investigate the effect of adding electricity storage to a community energy scheme. The Bethesda Energy Local Club is an energy cooperative in Bethesda in North Wales, comprising 100 households, run by Energy Local. The community is fed by a 100 kW micro hydro plant nearby. Each household has a smart meter that records their electricity consumption at 30 minute intervals. Historic data on the community's aggregated electricity consumption and the output of the hydro plant has been made available to the authors at 30 minute resolution through an API, and data over the period of 1st August 2017 to 31st July 2018 is used for the analysis conducted here. Throughout this period there were 100 households in the community. Monthly electricity generation and consumption totals are shown in Fig. 3; it can be seen that there is significant variation in the hydro generator's output from month to month, and that the hydro output reduces significantly over summer.

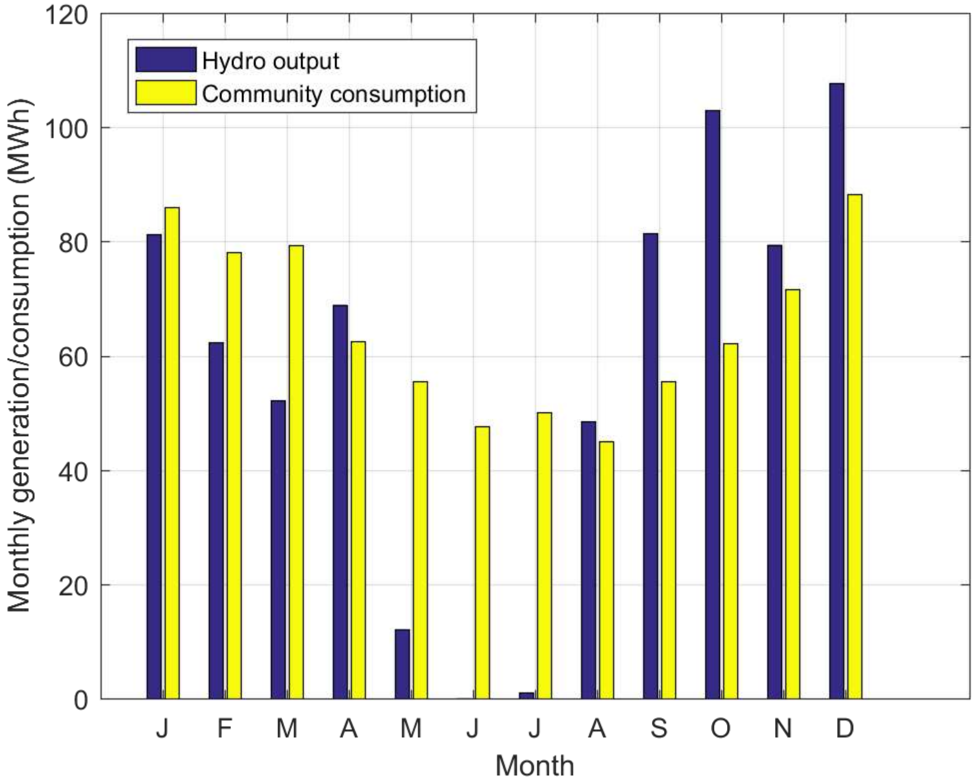

Fig. 3 Monthly hydro generation and community electricity consumption at the Bethesda Energy Local Club community energy scheme in Bethesda, North Wales, between August 2017 and July 2018.

All households are signed up to the same electricity tariff with a licensed electricity supplier for grid import, i.e. when the community's consumption exceeds the output of the hydro plant. This is a four-rate time-of-use (TOU) tariff, with four tariff periods over the course of each day: morning, midday, evening, and overnight. The households also pay to consume the hydro power at 7 p/kWh, a slightly lower rate than the lowest price in the TOU tariff. (The hydro generation is shared among the households using a fair share allocation, as detailed in ref. [38].) The community has a PPA with the supplier, and so sells excess hydro power back to the grid. This supersedes the export component of the Feed-in Tariff, and so the community is paid for all export to the grid and is not subject to the requirement to only charge the storage using FIT-eligible generation [33]. The hydro payments and export payments are kept by the generator, to cover running costs and provide a return for shareholders. In the case of community-owned generation, these payments can be used for community projects. In this work we consider the households and generator collectively (since installation of storage should be a positive investment for all), so the hydro payments, which pass from householders to generator and so are completely internal, cancel out and do not need to be included. The effective tariff is laid out in Table 1.

Tariff Component	Time Period	Price
Morning	06:00-11:00	12 p/kWh
Midday	11:00-16:00	10 p/kWh
Evening	16:00-20:00	14 p/kWh
Overnight	20:00-06:00	7.25 p/kWh
Export	All the time	6 p/kWh

Table 1 Electricity tariff seen by the Bethesda Energy Local Club community energy scheme. Correct as of January 2019.

Some statistics over the analysis period are shown in Table 2. Roughly two-thirds of the hydro generation was self-consumed within the community; increasing this figure will lower the community's electricity costs and carbon emissions. It can also be seen that the maximum import was equal to the maximum demand. This is because the output of the hydro generator gradually reduces towards zero between periods of rain, as can be seen in Fig. 4, and the hydro output happened to be zero at the half-hour of maximum demand (18:00-18:30 on 1st March 2018). Note that Fig. 4 is a subset of the full dataset, shown as an illustration.

Analysis period	1 Aug 2017 – 31 Jul 2018
Number of households	100
Hydro generation capacity	100 kW
Total elec. consumption	782,118 kWh
Total hydro generation	697,956 kWh
Total grid import	311,624 kWh
Hydro self-consumption	67.4 %
Maximum demand	115.7 kW
Maximum import	115.7 kW
Maximum export	81.6 kW

Table 2 Statistics on the Bethesda Energy Local Club community energy scheme data used in this case study.

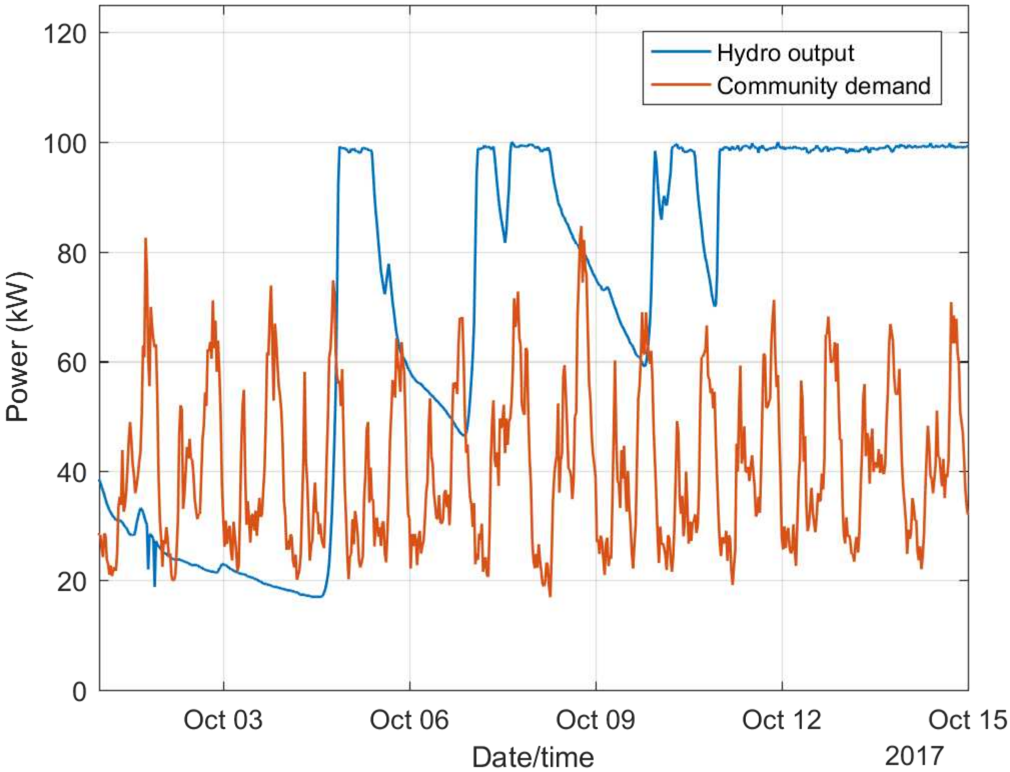

Fig. 4 Hydro output and community demand at the Bethesda Energy Local Club community energy scheme, over the first two weeks of October 2017.

Households in the community scheme have access to a website which provides information on the community's recent demand, along with the output of the hydro generator. Forecasts of upcoming demand and generation are also provided; the demand forecast is based on the same day in the previous week, and the generation forecast is based on a weather forecast. These data are currently used to provide households with advice regarding when to run appliances in order to save money.

The characteristics of the energy storage systems considered in this case study are laid out in Table 3. The charging and discharging efficiencies of the Li-ion battery system are calculated as the square-root of 85%, a typical round-trip efficiency for a Li-ion battery system [39]. The charge and discharge power capacities for the reservoir storage system are as explained in Section 2.2; charge power capacity is given as not applicable as it is assumed that the reservoir can be charged at any rate up to $g(k)$, i.e. up to the rate at which energy is flowing through the hydro generator.

	Li-ion Battery	**Reservoir**
Charging Efficiency	92.2 %	100 %
Discharging Efficiency	92.2 %	100 %
Self-Discharge Rate	0.3 %/day	0.3 %/day
Charge Power Capacity	0.5 C	N/A
Discharge Power Capacity	0.5 C	100 kW
Calendar Life	15 years	40 years
Cycle Life	20 % capacity fade	N/A

Table 3 Characteristics of the energy storage systems considered in the case study.

In this study, we look at the economics of adding electricity storage to the existing community, as well as at the potential to increase the community size using storage.

3.2. Existing community size

We begin by determining the NPV of behind-the-meter storage systems at the Bethesda Energy Local Club community hydro scheme, applying the linear programming methodology developed in Section 2. NPVs are shown in Fig. 5 for Li-ion battery storage and reservoir storage, over a range of sizes and capital costs. Breakeven storage costs are shown in Fig. 6. At this point, no grid import constraint (equation 14) is applied. When modelling reservoir storage, the constraints defined in equations 15 and 16 are included. A discount rate of 6% is used in all cases; this is higher than the social time preference rate of 3.5% (recommended for use by the UK government in appraisal of public sector projects [40, 41]) to account for the systematic risk associated with new energy projects. Evidently, while the installed cost of battery storage is in excess of approximately £200 per kWh of storage capacity, the NPV is negative with all levels of installed capacity. If the cost of storage falls below this level, then the optimal installed capacity depends upon the storage cost; the lower the storage cost, the higher the optimal installed capacity. For any given storage cost, the available annual savings gradually level off with increased storage capacity, as the number of remaining opportunities for cost savings diminishes.

These results show that the cost savings from using battery storage at a community hydro scheme are so low that a battery storage system is not economically viable with current battery costs and electricity prices. The results show that in order to be cost-effective currently, behind-the-meter battery storage should also be used to provide grid services (such as frequency response, operating reserve, and network support) in addition to increasing the self-consumption of embedded generation and arbitraging on electricity tariffs. However, with the current pace of cost reductions [42], battery storage could be economically beneficial in community energy schemes even without providing grid services in a few years' time.

It is also evident that for any given capital cost of storage, a reservoir storage system has a higher net present value than a battery storage system of equal energy storage capacity. There are three factors contributing to this. Firstly, a dam/reservoir has a much longer lifespan than a battery: 40 years vs 15 years in the analysis presented here. Secondly, at all storage capacities, the reservoir can be charged using all of the flow that would otherwise be passing through the hydro generator and can be discharged at any rate up to the power capacity of the generator (i.e. 100 kW in this case), whereas a battery is limited by the charging and discharging power capacities, both set to 0.5C here. (A battery has a benefit of being possible to charge at any time, however on-site generation is typically lower cost than grid power.) Finally, the charging and discharging efficiencies of a reservoir storage system are higher than with a battery.

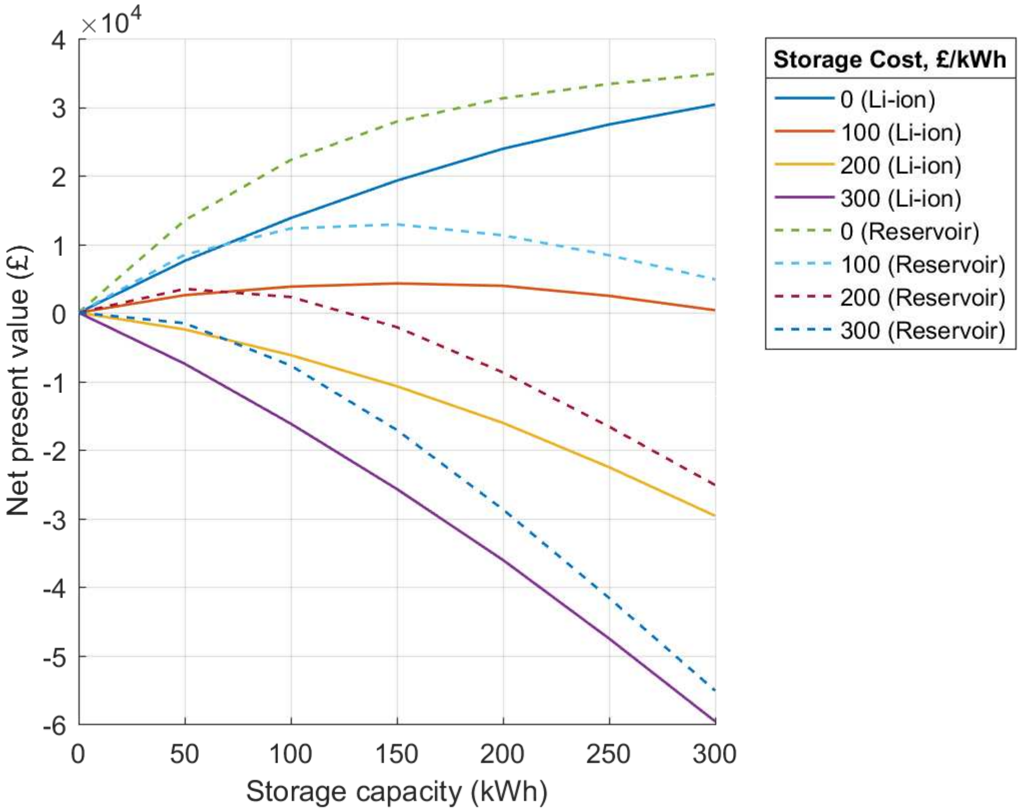

Fig. 5 Net present value of a Li-ion battery energy storage system and a reservoir-based generation-integrated energy storage system at the Bethesda Energy Local Club, for a range of storage capacities and capital costs. Battery life: earlier of 15 years and 20% capacity fade. Reservoir/dam life: 40 years. 6% discount rate.

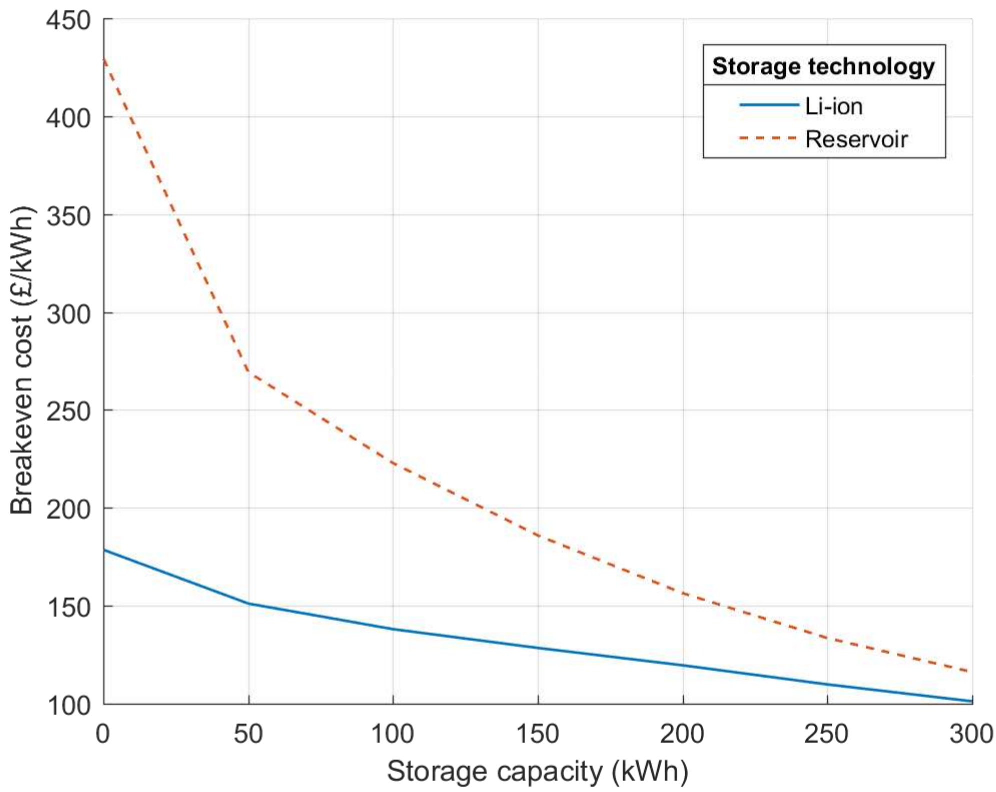

Fig. 6 Breakeven cost of storage for the systems presented in Fig. 5.

In all cases, the cycling-induced capacity fade of the battery in the first year of operation is small, in the range of 1-3%. The percentage capacity fade is highest in systems with small storage capacities because such systems undergo a greater number of cycles, and hence the cell-level charge throughput A_h takes a higher value in equation 17. Since Q_{loss} is concave in A_h, the rate of capacity fade reduces over time, and so the capacity fade in subsequent years is less than in the first year. After 15 years of operation, battery capacity fade was less than 20% in all of the cases studied for Fig. 5.

An example of the operating schedule developed using the linear programming methodology, for a 100 kWh battery energy storage system, is shown in Fig. 7. It can be seen that charging is prioritised when there would otherwise be excess hydro power, and that discharging is prioritised during the morning and evening peak periods. Demand exceeds generation for most of the first two days, during which time the storage cycles to arbitrage on price differences in the time-of-use tariff. This increases grid import to such an extent that the daily peak grid imports are shifted into this period in each of the first two days and considerably increased; known as a "rebound peak", this phenomenon has been found previously [20, 43]. The storage operates very little during the last two days, as the hydro generation exceeds the community consumption throughout most of this period leaving very few occasions when storage discharge is worthwhile.

Because the rate of self-discharge is proportional to state of charge, the optimisation seeks to maintain a low state of charge where possible, and hence when there is a range of times during which a charging operation could occur with equal cost at any of the times in the range (e.g. during the 10-hour overnight price period), the charging operation will take place as late as possible. Similarly, discharging occurs as early as possible.

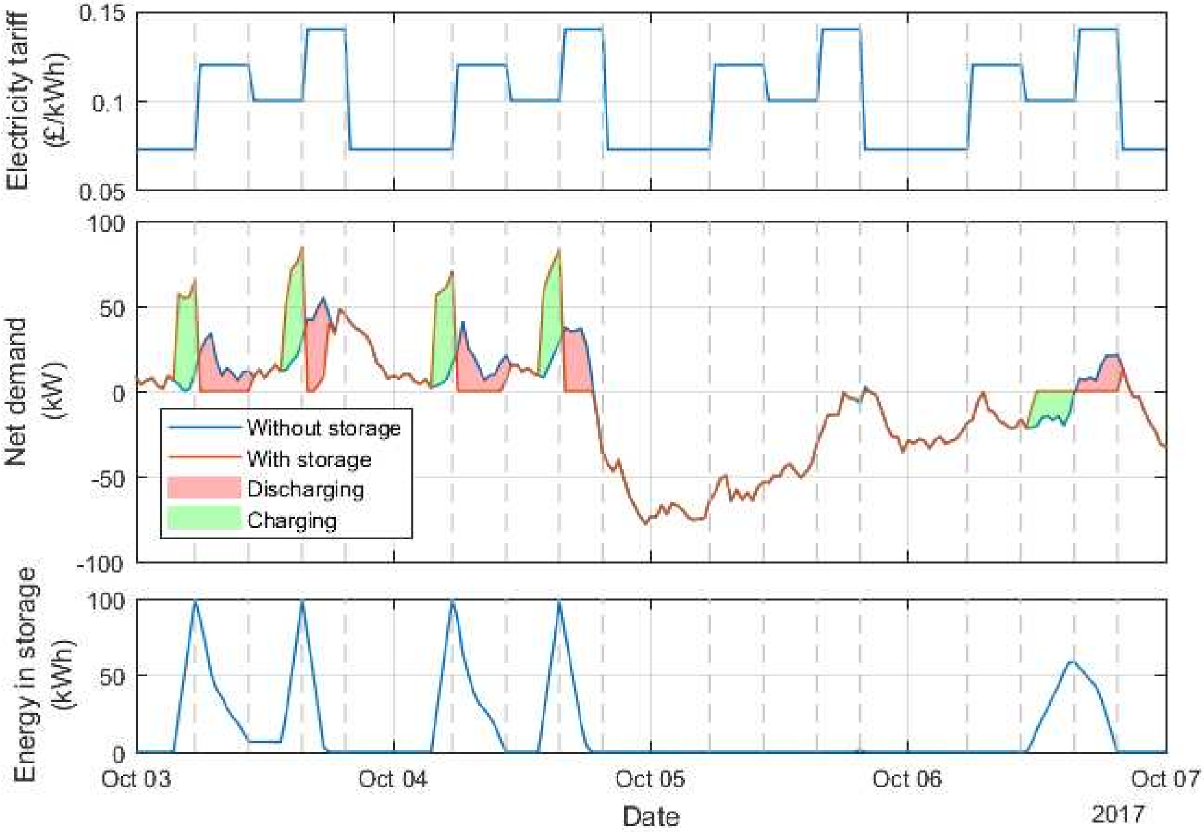

Fig. 7 Storage operating schedule over four days in October 2017, for a 100 kWh Li-ion battery storage system. Positive values of net demand correspond to import from the grid, negative values correspond to export to the grid. Times of tariff price periods marked using grey dashed vertical lines.

The effect of behind-the-meter storage on carbon emissions is shown in Fig. 8, assuming that the storage is operated to maximise NPV. We simply use the charge/discharge schedules developed for the results shown in Fig. 5 and Fig. 6. These schedules are used to find grid import $\boldsymbol{p}^{+}$, and equation 20 is applied. It can be seen that increased levels of storage capacity generally lead to a reduction in CO_2 emissions, as a result of increased self-consumption of hydro and hence reduced grid import. However, in the case of a battery system that can be charged from the grid, CO_2 emissions actually increase by a small amount as storage capacity is increased from 100 kWh to 150 kWh, then decrease again with further increases in storage capacity. This increase occurs because, above around 50-100 kWh of storage capacity, the best opportunities for self-consuming hydro and then discharging in peak periods have all been used up, and the next best opportunities for cost savings result from charging from the grid (hence increasing grid import and CO_2 emissions). As storage capacity is increased further, the next best opportunities for cost savings then arise from further self-consumption of hydro. Reservoir storage only leads to a reduction in CO_2 emissions because it cannot be charged from the grid (unless the reservoir is part of a pumped storage system, of course).

Clearly, the cost of reducing a community's carbon emissions by adding energy storage alongside an existing renewable installation is very high, at hundreds of times the level of existing carbon prices (for example in the EU Emissions Trading Scheme and UK Carbon Price Floor). By way of example, even if the capital cost of battery storage could be reduced to £100/kWh, a 50 kWh system, saving one tonne of CO_2 per year, would cost £5,000. This is on the order of 100 times higher than most projections of carbon prices by 2030.

In reality of course, embedded renewables are not curtailed and exported electricity is often used in the local area anyway, so the losses associated with exported renewable generation are low. However, it should be remembered that energy storage is not a generation technology, but is instead an enabler for low carbon generation.

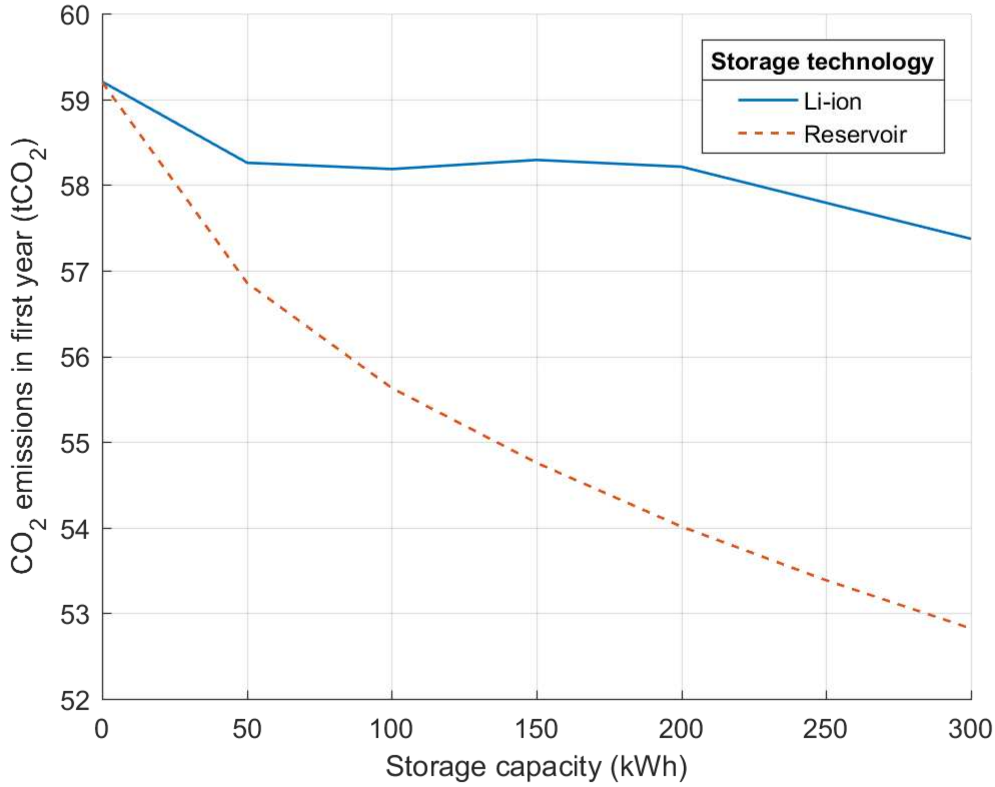

Fig. 8 CO_2 emissions in first year of operation.

3.3. Increasing the community size

The linear programming optimisation framework developed in the previous section is used to determine how much electricity storage is required to maintain the maximum import of the community at the existing level of 115.7 kW while the community load is increased by adding more houses. Again, storage schedules are developed assuming that the storage is operated to maximise NPV, but a grid import constraint is now included using equation 14, setting M = 115.7 kW. We make the assumption that an n % increase in the number of houses in the community causes an n % increase in demand at all times. This is a fair assumption because with 100 houses already in the community, the diversity in living patterns is already well accounted for; the design standard of a large Australian utility states that After Diversity Maximum Demand (ADMD), which represents the maximum electricity demand of a group of consumers divided by the number of consumers, is valid at distribution substations where there are at least 60 consumers connected to that substation [44]. This suggests that the diversity in living patterns is accounted for when there are more than 60 consumers.

The maximum number of households in the community (while keeping maximum import unchanged) is shown against battery storage capacity in Fig. 9, for various maximum charge and discharge C rates. From Fig. 9, it is clear that with C rates of 0.5 and above, the storage capacity required to keep the maximum import unchanged increases more than linearly with number of households in the community. As the number of households is increased, the number of half-hours in which the previous maximum import of 115.7 kW is exceeded increases until, with a large enough number of households, even the minimum import will exceed 115.7 kW, at which point it is clearly impossible to use storage to keep the maximum import below 115.7 kW. As a result, it is not surprising that an asymptote is exhibited.

Evidently, if the maximum C rates can be increased from 0.25 to 0.5, then membership of the community hydro scheme can be increased. It is also clear that with storage capacities greater than about 60 kWh, increasing the maximum C rates above 0.5 provide no further gain in terms of allowing increased numbers of households to join the community.

We see that with a storage capacity of 100 kWh, we could expect to increase the number of households in the community from 100 up to 131. However, it is important to note that these results assume perfect foresight of half-hourly demand and generation up to 96 hours hence. In reality, imperfect forecasting will mean that such high increases in membership of the community energy scheme will not be possible, and the results shown here represent something approaching the best case.

The allowable growth in the community energy scheme membership through the addition of reservoir storage initially matches that from adding battery storage, but then tails off at higher levels of storage capacity. This is because the reservoir storage can only be charged using water that would otherwise pass through the hydro generator, whereas battery storage can either be charged using hydro generation or from the grid.

From this case study we can conclude that reservoir storage at a community hydro scheme has higher NPV than a battery of equal storage capacity and capital cost, and leads to higher reductions in operational CO_2 emissions. However, this must be weighed up against the relative simplicity of adding a battery storage system, which has simpler planning requirements than reservoir storage and can be sited almost anywhere. Battery storage also has better growth-enabling capabilities than reservoir storage, particularly at high levels of energy storage capacity and when the battery has high power capacities, allowing a greater number of households to be connected to a given network.

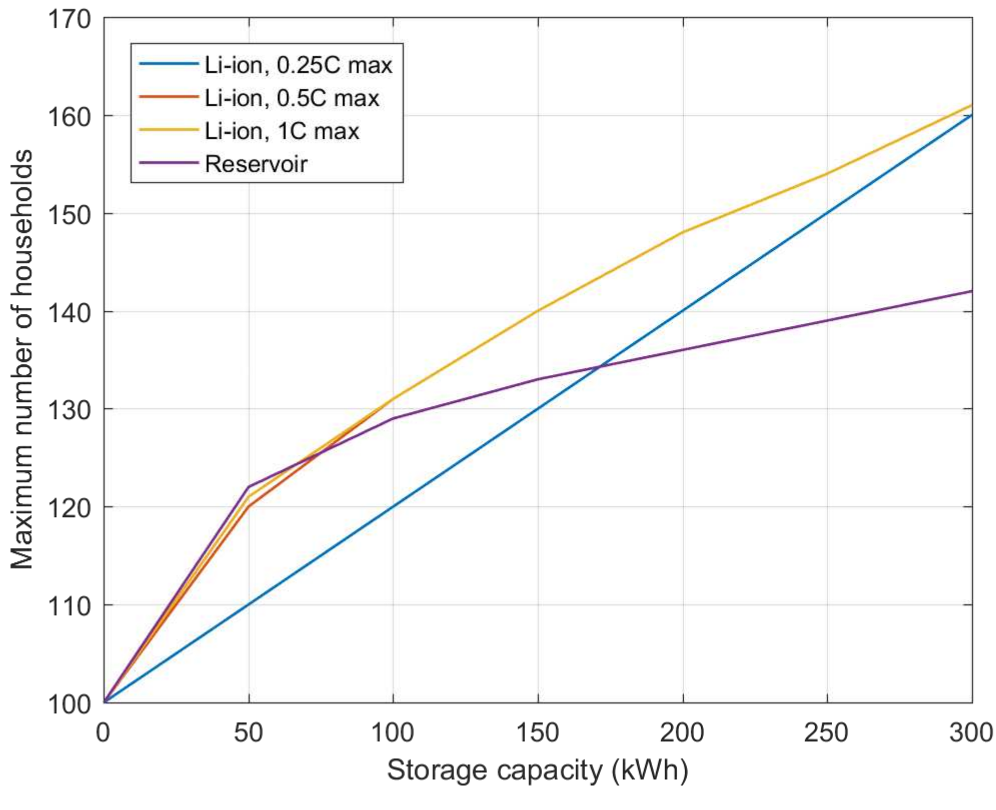

Fig. 9 Maximum number of households that could be in the community against the energy storage capacity required to keep the community's maximum grid import

power unchanged from its current level. Maximum C rates are for both charge and discharge.

3.4. Other possible applications

In this section, we have applied the methods presented in Section 2 to analyse the value of energy storage in a community hydro scheme featuring a hydro generator and a collection of nearby houses across which the hydro generation is shared. Both non-generation-integrated energy storage and generation-integrated energy storage systems have been considered, in the form of battery storage and reservoir storage respectively. We conclude this case study by giving a brief discussion of other possible applications for the analysis methods.

Another typical example of a community energy system is a community solar PV scheme, whereby solar PV generation is shared amongst scheme members. Analysis of such a system could be conducted using the non-GIES modelling approach, with the community generation $\boldsymbol{g}$ simply being the output from the PV array. In such a scenario it might also be important to limit peak export, in which case an additional constraint on $\boldsymbol{p}^{-}$ would be included, similar to the import constraint of equation 14.

With little modification, the methods could also be used to investigate the operation of storage alongside standalone generation (i.e. no co-located demand), such as a wind farm with co-located storage, and standalone storage (i.e. no co-located generation or demand). For storage alongside standalone generation, co-located load $\boldsymbol{l}$ would be set to zero, and for standalone storage both $\boldsymbol{g}$ and $\boldsymbol{l}$ would be set to zero. In both of these cases it is possible that the storage would be operated according to wholesale electricity prices, in which case the electricity price vectors $\boldsymbol{\lambda}$ and $\boldsymbol{\pi}$ would be set to day-ahead or intra-day prices. As mentioned previously, the methods could be used for real-time storage scheduling based on forecasts of local demand, local generation, and electricity prices, in which case $\boldsymbol{\lambda}$ and $\boldsymbol{\pi}$ would be set to price forecasts.

The methods could also be used to study other generation-integrated energy storage systems, such as concentrated solar power with molten salt storage [45], thermal energy storage integrated with nuclear power [46-48], and pumped heat electricity storage integrated with wind power [15]. Thermomechanical storage systems are often characterised by slower response rates than electrochemical storage, and storage ramp-up and ramp-down constraints could be easily included using inequality constraints of the form $\boldsymbol{Au} \leq \boldsymbol{b}$, ensuring that $u(k+1) - u(k)$ is between the allowable ramp-up and ramp-down rates.

4. Conclusions

For the first time, this paper set out to compare the value of generation-integrated and non-generation-integrated energy storage systems in community electricity generation schemes. A range of areas were investigated, including economics, carbon emissions, and distribution network support. To accomplish this objective, an efficient approach to storage scheduling was developed and applied to a case study of a community hydro scheme in rural North Wales.

It was demonstrated that the addition of energy storage to community energy schemes could provide benefits. Most importantly, storage could allow scheme membership to be increased with no impact on the electricity network. At the case study hydro scheme, with 100 households and a 100 kW hydro generator, the addition of 100 kWh of Li-ion battery storage would allow the membership of the scheme to be increased by a third. Greater installed capacities of storage would allow even more members to be added. It was found that GIES systems generally cannot allow scheme membership to be increased by the same level as non-GIES systems. This is because the storage in GIES systems cannot be charged from the grid, and is entirely reliant on the availability of energy from the local generator.

Adding storage to a community energy scheme would generally be expected to increase the self-consumption of on-site renewable generation and hence reduce grid import and associated carbon emissions. Our analysis demonstrated that the impact on overall carbon emissions at the case study location was low, with 200 kWh of Li-ion battery storage only reducing the community's annual carbon emissions by an additional tonne of CO_2 (at a scheme with a 100 kW hydro generator and 100 households). At this level of 10 $kgCO_2$ per household per year, this is only around 0.5% of an average UK household's electricity-related CO_2 emissions [49]. This is a disappointing result, indicating that storage deployed in the manner set out here will not provide a significant carbon benefit.

A GIES system leads to greater reductions in CO_2 emissions than a non-GIES system; in the case presented here, a 200 kWh reservoir storage system would provide approximately five times the emissions reduction provided by the equivalent battery storage system. This is because a GIES system can generally only be charged using energy from a low carbon source (in this case the energy in a mountain stream), whereas a non-GIES system is sometimes charged using grid power, a component of which is fossil fuel generation. As with much work in this area, the calculation approach employed relies on some simplifications. We therefore present a methodology that will allow us to account for time-varying grid carbon intensity in future work, drawing on some data only recently available for the UK.

Depending upon the installed storage capacity, the breakeven cost of Li-ion battery storage at the scheme was around £150/kWh, whereas the breakeven cost of reservoir storage would be around £250/kWh. While the costs of battery storage have dropped considerably in recent years, driven largely by increased demand for consumer electronics and electric vehicles, they remain above this level. As a result, there is currently no strong economic case in the UK for the adoption of battery storage at community energy schemes, based on income from electricity arbitrage or possible future income derived from carbon savings. Currently the only route to acceptable economics is if the developer can ensure that lucrative grid services can also be provided using the battery [50], an option not analysed here. However, given past trends in battery costs, it is likely that battery storage will be economical when used for electricity price arbitrage in a few years' time.

The generation-integrated storage approach offers a better breakeven cost than battery storage in this case study. In large part this is because a reservoir system has increased power capacities and a longer lifetime than a battery storage system. In forming a judgement as to which is the superior approach, this must be tensioned against the difficult-to-estimate, and highly location-specific, costs of increasing reservoir capacity. Equally the GIES approach in this case would not be able to access potential income streams associated with high frequency grid services, in contrast to a battery system, and its ability to allow increased membership of a community energy scheme without increasing the grid connection capacity is lower than that of a battery system, because it can only be charged using primary energy and cannot be charged from the grid. Nevertheless this result, combined with previous research demonstrating high roundtrip efficiencies [8], demonstrates that GIES should be investigated further for integration with community energy schemes.

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