Abstract

Energy storage (ES) is seen as the key to unlocking the true potential of renewable generation as it potentially supports their integration into the grid by providing capability for services such balancing and frequency regulation. It also has the potential to reduce peak power demand reduction (a form of arbitrage) and this service will be important for distribution companies as it frees capacity on the grid. The first part of this study presents an energy management strategy (EMS) that reduces the peak power drawn from the grid by a community of 60 homes using ES and local generation (in this case photovoltaic panels (PVs)). The EMS is tested on hundreds of cases and shows an average yearly peak reduction of around 30% in the best cases. The second part of the paper tests the economic viability and greenhouse gases (GHG) emissions of the cases explored and shows that trade-offs exist between electricity supply costs, peak power reduction, and life cycle GHG reductions. PV generation provides a significant reduction in GHG emissions but makes little contribution to reducing peak demand from the grid. In contrast, community energy storage (in batteries) is effective at reducing peak demand, but at significant additional costs, and may result in a modest increase in GHG emissions due to emissions associated with battery manufacture and roundtrip efficiency. Future cost projections for 2040 for PV and battery, together with longer a battery cycle life, show that considerable reductions in the cost of community electricity generation and storage can be made to encourage the management of peak grid demand.

Techno-economic and environmental analysis of community energy management for peak shaving.

Matteo Cossutta[a-b]*, Seksak Pholboon[c], Jon McKechnie[d], Mark Sumner[c]

*Corresponding author

[a] Faculty of Engineering, University of Nottingham, Nottingham NG7 2RD, UK
matteo.cossutta@nottingham.ac.uk*
[b] Aria Sustainability Ltd Unit 24 Wilford Business Park, Ruddington Lane, Nottingham, United Kingdom, NG11 7EP
[c] Department of Electrical & Electronic Engineering, The University of Nottingham, Nottingham NG7 2RD, UK – ezasp12@exmail.nottingham.ac.uk – mark.sumner@nottingham.ac.uk
[d] Sustainable Process Technologies, Faculty of Engineering, Faculty of Engineering, University of Nottingham, Nottingham NG7 2RD, UK - Jon.mckechnie@nottingham.ac.uk

1. Introduction

During the last decades, global warming caused by greenhouse gas (GHG) emissions has become an increasing cause for concern and part of the political agenda of most of the world's nations. The "Paris climate agreement" of 2015 was part of the global strategy to tackle climate change and one of the essential steps towards this goal is the switch from fossil fuels energy to renewable energy [1]. The UK government has set the renewable energy target to be delivered as 15% of the total energy demand by 2020 [2] and consistently reduce overall GHG emissions by 2032 as planned in the 5th carbon budget [3] and reach net-zero emissions by 2050 [4]. Onshore and offshore wind and solar photovoltaic are among the fastest growing renewable electricity generation in comparison to alternatives. In 2019, they accounted for 64.1 percent share of the total renewable generation in the UK [5]. These sources, however, are intermittent in nature, which could pose a challenge to the distribution systems in terms of the grid stability and reliability.

Deploying energy storage is one of the solutions proposed to help integrate these renewable sources into the grid [6, 7]. The use of energy storage (ES) systems at community scale has recently seen considerable interest from the research community, as it can potentially address the reverse power flow problem and provide better regulation of system voltage. It may also provide a mechanism to aid in the foreseeable increase in electrical loads (electric vehicles, heating, ventilation and air conditioning) without the need for upgrading the distribution system infrastructure [8, 9]. However, while ES coupled with photovoltaics (PV) can increase self-consumption reducing the use of fossil fuels for electricity generation, the environmental benefits should not be outweighed by the ES production and use phases. Thus, a life cycle assessment (LCA) is necessary to understand the overall system sustainability. Economic viability is also crucial since no investment in ES is made if not economically profitable. Both the LCA and the economic analysis are very dependent on how the system is designed and operated so it is important to couple them with a technical analysis aiming at finding an optimal configuration that minimises costs and maximises the technical and the environmental performance.

Several technologies for storing energy are under research or deployed, for example pumped hydroelectricity storage, compressed air, flywheels, supercapacitor, superconductive magnetic energy storage and all sort of batteries to name a few. They have different purposes and can store different quantities (and types) of energy, but when dealing with residential storage, especially if coupled with PV, most of the literature focuses on the use of batteries [10-13] for increased self-consumption and peak-shaving. To achieve these two goals, advanced energy management strategies must be in place and much research has been published on this topic over the last decade.

In most of the studies, the electricity price is used as main objective of the control optimization since it reflects the peak demand defined by the distribution network operator (DNO). Following this method, [14-16] presented a dynamic programming (DP) approach, [17, 18] used a linear programming (LP) and mixed integer linear programming (MILP) approach, and [19-21] proposed a model predictive control (MPC) technique. Other research disregards the electricity price and use a direct way to reduce the peak demand. For example, [22, 23] use a low-pass filter based simple moving average (SMA) technique where the high frequency component determines the operation of the battery energy storage. This however suffers from low frequency profile lagging and forecast error which reduces the performance of the battery. Pascual et al. [24] proposes a central moving average (CMA) approach to eliminate the lagging effect and uses the battery state of charge (SOC) feedback to deter the forecast error. This approach reduces the optimization complexity, but the use of energy storage is limited because it requires its oversizing to achieve daily demand smoothing. Others adopt the power pinch analysis (PoPA) concept to shift the load demand and manage the energy storage

[25-27]. This is a simple technique that works effectively with fixed or predictable load requirements [26].

Research has also focused on techno-economic aspects of using batteries, and other energy storage technologies, for several different purposes [28, 29], including energy management at residential community scale or single house [30-35] or commercial buildings [36]. Different types of batteries are often investigated but most of the focus is on lithium ion (Li-ion) and lead acid. Between the two, the lowest cost choice is dependent on the application, however uncertainties in their technical parameters (i.e., cycle life, calendric life, round-trip efficiency) and other costs (i.e., balance of plant, power conversion system (PCS), operations and maintenance) exceed the difference in costs, making this a topic for further studies [30]. Lead acid batteries are a mature technology, but with a lower energy and power density than Li-ion batteries (not an issue for stationary application). However, Li-ion could become the favourite technology when prices decrease due to their higher energy efficiency and aging features [28, 37]. Methodologies using linear optimisation are proposed to find the most advantageous component sizes for residential battery storage showing effective results in maximising the electricity cost savings while minimising the storage degradation costs [38]. Pinch analysis is also used to identify appropriate storage options in relation to the community needs [39]. Some studies focus on analysing different energy management strategies to maximise self-consumption or maximise peak-reduction in order to evaluate their impact on the system costs [40] and their results show that energy storage is generally found unprofitable [31, 35, 36] unless it provides several paid services on different markets (capacity, frequency regulation, balancing, energy arbitrage, network support, wind support etc.) [41].

The environmental impacts, mostly GHG emissions, of PV and battery production are also broadly investigated. Several LCA of PV were performed as shown by the review of Nugent et al. [42] and Gerbinet et al. [43]. The environmental impacts of batteries has also been investigated with LCA, and of the different technologies, the Li-ion one is found to be the least impacting in delivering 1 kWh of electricity for different stationary applications when accounting for manufacture and use phase [44]. The techno-economic and the environmental aspects are rarely combined although welcomed [31, 45]. One study from Abdon et al. [46] comparing different energy storage technologies found that batteries are the cheapest solution for short time scale (minutes) but also with applications for medium time scale (4 hours). Moreover, batteries show low impacts for global warming potential (GWP) compared with other type of storage.

Only one study was found that offers a combination of techno-economic and environmental analysis for PV and community storage. It shows the benefits of installing PV and storage from both the environmental and economical perspective [47] even though it stresses the problem of the large initial investment with a long payback time (up to 14 years). To the best of our knowledge, no previous study provides a techno-economic and environmental evaluation of a configuration of PV and storage that adopts a novel energy management strategy (EMS) aimed at maximising peak-shaving to allow for more spare capacity on the grid. In other words, the batteries are not charged primarily when the electricity price is lower, but when necessary to have them ready to shave the peak demand. Secondarily, this study evaluates the results from the retail market perspective.

The aim of this paper is, therefore, to provide an optimal solution for peak shaving while aiming at reducing the overall cost from a wholesale perspective (i.e. lower the cost of electricity at wholesale market price) and environmental impacts for the community. This study introduces a novel battery management strategy for a grid-connected energy storage system with PV for a community of 60 homes based on a combination of the PoPA technique and the battery SOC feedback closed loop control. This novel strategy is applied to different battery and inverter sizes and different number of

PVs installed to find an optimal solution for the community. A techno-economic and environmental analysis is also performed on all scenarios with the aim of finding a trade-off among the technical performance, the cost, and the environmental impacts.

2. Methodology

The electricity consumption profiles of a small community have been investigated to better understand the trade-offs between investment costs, environmental impacts, and the influence of an energy storage system (ESS) on the community's electricity usage. The community is made up of 60 dwellings, and its consumption over a full year has been analysed, with different amounts of installed local PV generation, and different sizes of energy storage system. The profiles with and without the PV and ESS are obtained from simulation studies, and the following sections describe the energy management strategy, the data sources and the prediction algorithms used to forecast consumption and generation in these studies. The methodology of the analysis and comparison will then be described. Before doing this, though, it is necessary to define an EMS.

The EMS controls the operation of the ESS so that the electricity consumption of the community follows a specified trajectory to fulfil three control objectives. These objectives are to minimise the reduction of the power drawn during peak consumption periods (peak shaving), reduce the cost of power drawn from the supply utility and to maximise self-consumption of locally generated power (i.e. from PV systems). A real time pricing tariff together with predictions of future demand and generation are used to create a profile for the desired half-hourly community power consumption for the next day. The PoPA then optimises this target based on knowledge of battery capabilities and an objective rule-base to guarantee daily power smoothing. To account for system losses and prediction errors in real time, a faster control loop is employed which compares the desired profile with the measured community power flow on a minute by minute basis and modifies the ESS commands to ensure desired profile is followed correctly.

This proposed strategy therefore offers a simple and robust approach to EMS implementation, but to check its effectiveness, a techno-economic and environmental analysis has been performed. More than 300 scenarios were analysed where different sizes are used for the PV array, power conversion system (PCS) and battery capacity, to understand how these parameters affect the peak-shaving performance, self-consumption and electricity costs for the community. For each scenario, GHG emissions and equipment costs are calculated and annualised on the equipment lifetime bases. The best performing scenarios in terms of peak-shaving, electricity and infrastructure cost, and GHG emissions were selected and compared to understand the trade-offs between these factors.

2.1 Energy Management Strategy

The EMS achieves the tree main objectives by controlling the net power drawn from the main grid by the community on a minute-by-minute basis. This net power (called here the "Community Power Flow" or CPF) is a combination of the community's consumption and PV generation together with any charge (discharge) of the community's batteries, and therefore it is the battery that is controlled to achieve the objectives.

The proposed strategy consists of three control layers as shown in Figure 1. The first layer aims to determine the best target for the community's CPF – here called the Community Power Flow target or CPFT. It sets a profile for the CPFT for a day ahead with the objectives of reducing peak load (peak demand shaving), demand smoothing and increasing the self-consumption of locally generated renewable energy. The calculation of this CPFT uses knowledge of the community's previous energy usage, its previous renewable energy generation, real time pricing (RTP) from the electricity markets, and also knowledge of the battery's operating condition (capacity, state of charge, maximum power capability). These prices are used because the RTP normally reflects when peak power demand occurs (i.e. high price periods) and when it is financially beneficial to reduce consumption from the grid. This first layer calculates the best power consumption profile (CPFT) for the next 24 hours by means of an autoregressive predictive model using the data from same day of the week before. It is assumed that patterns of behaviour within the community follow weekly rather than daily patterns.

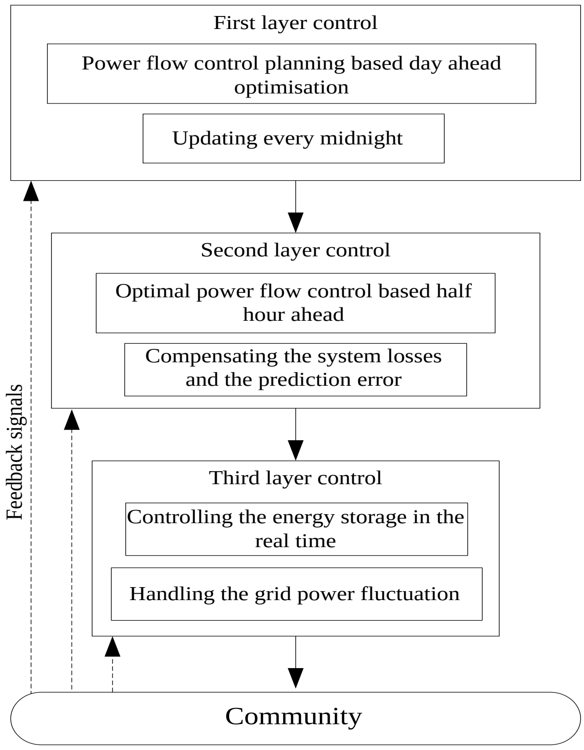

Figure 1 – Community energy management strategy: three control layers

The second layer takes the CPFT obtained from the first layer for the next half hour period and modifies it using feedback from the battery – its state of charge (SOC) – to adjust for system losses and prediction error. This means that any deviation of the predictive first layer from the real consumption of the community is corrected for the next half hour. To do this, the second layer uses the same auto-regressive prediction technique but with a half hour time resolution and always for the same half hour of the same day of the week before.

The third layer forces the grid demand to follow the CPFT by charging or discharging the battery based on the residual energy between the CPFT and actual community power flow. It runs in real time with a one-minute sample time and by evaluating the difference between the load predicted by the second layer and the real load, it decides whether to charge or discharge the battery. More details on the three layers are available in the supporting information (SI) in section S1 and S2.

2.2 Load and PV energy forecasting

There are many load forecasting methods that have been reported over the last decade from simple persistence based methods [24], which select historical data from a similar day for use as a prediction, to more complex methods such as those using mathematical models with time series, artificial neural networks, fuzzy logic, expert systems or statistical learning algorithms [48, 49]. In this work, a time series method based autoregressive model (AR) is used to predict the load and PV generation profiles. This method is relatively simple and has the advantage of only using historical data in the prediction i.e. the predicted load is assumed to be a linear combination of previous loads. To improve the prediction accuracy, the coefficients of the AR model need to be obtained using a training algorithm and data collected from the community and PV generation. For the load forecast model, the training data is based on the same day of the week and also the season (as consumption patterns can vary seasonally). For the PV prediction, the data from the same month in the previous year is used to train the PV prediction data.

To test the effectiveness of the strategy for different prediction approaches three approaches have been evaluated through simulation, namely 1) persistence (PS – uses the same values of the week before), 2) autoregressive (AR – uses the autoregressive approach tested in this analysis) and 3) perfect foresight (PP – use perfect data prediction, impossible in real life).

2.3. Data Sources

The EMS has been evaluated by applying it to the control of an ESS in a community of 60 dwellings. The real time pricing tariff, which has a half hour price variation, can be obtained from the New Electricity Trading Arrangements (NETA) website [50].

The community load profile considered is based on the real measurement of sixty residential dwellings in Milton Keynes, UK [51]. The load dataset provides a minute-by-minute profile for electricity power consumption for the whole year. PV generation is included for most of the simulation scenarios and the PV profile used for these studies was obtained from actual power data measurements recorded with a sample rate of 10-minutes available at www.pvoutput.org.

The power converter model used in this work is characterised from empirical data obtained at the University of Nottingham. A 12kW DC-AC power converter was tested across a range of operating powers to determine how its efficiency changes as a function of power processed. The converter was then modelled using the efficiency curve fit presented in the SI section S3 and its minimum operating limit set at 10% of its rating to maintain an efficiency of at least 88%.

The battery model is based on measurements performed at the University of Nottingham on a 24 kWh lithium-ion battery pack. By cycling the battery and measuring the voltage and current at the battery terminals the battery open-circuit voltage (V_{oc}) and battery internal series resistance (R_{batt}) can be determined, indicating roundtrip efficiency of charging/discharging battery under various conditions (see SI section S4 for details). The parameters used to describe the battery state are the instantaneous values at the battery terminals. The battery voltage changes with the battery state of charge. This parameter will determine the maximum charge and discharge power of the battery as well as the maximum battery capacity. The battery SOC is kept between 10% and 90% to prolong its lifetime as recommended by [52] to maximise battery life. Note that the battery capacity and power rating of the converter will be varied as part of the techno-economic analysis described in the next section.

2.4 Modelling

The community is modelled using a bespoke MATLAB program which inputs consumption and generation data on a minute by minute basis and combines this with the modelled charge/discharge of the battery to obtain the community power flow for that minute. The EMS layers are executed at their appropriate sample times. A full year is simulated for each scenario so that it can be compared with the baseline scenario of the community without PV or ESS. To illustrate the data that is presented from this simulation, Figure 2 shows the data for three days resulting from a typical simulation.

This scenario is for three consecutive typical summer days for a scenario in which 10 community houses have PV panels installed (3.89 kWp each) together with a battery system rated at 147 kWh and a 50 kW power converter. The top graph shows the community power flow (red) with no battery, the PV generation (green) and the community power flow when the battery and the proposed algorithm is used (blue). The bottom graph shows the battery's state of charge. The chart shows that the battery pre-charges by a small amount from the grid overnight (low cost energy) and then discharges during the early morning peak. Then the battery starts to charge from approximately 9.00 hrs using surplus PV energy (i.e. PV generation in excess of local load requirements) to store sufficient energy to be ready for discharge during the evening peak period. An important point to note is that export seen in the red trace (negative grid power) is virtually eliminated in the blue trace i.e. the battery has ensured that the community can consume all of its locally PV generated energy.

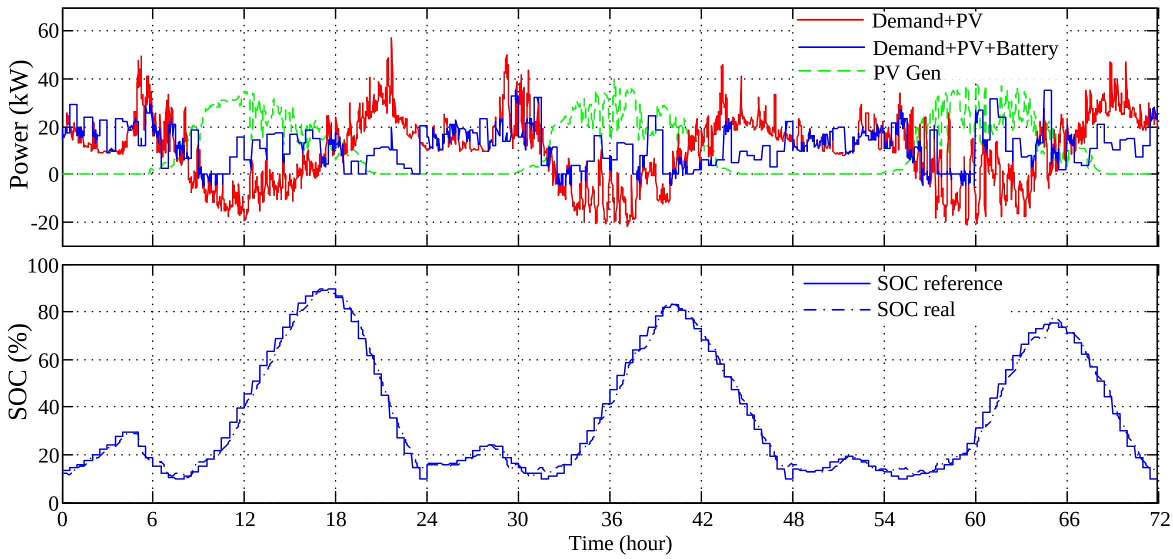

Figure 2 – Typical Simulation results
Community demand and PV generation profiles (Top) and SOC (Bottom) on typical days in July

By comparing the red and blue traces, the ability of the battery to move energy from high tariff to low tariff periods can be quantified – this is termed "peak demand reduction". The peak demand reduction is calculated by determining the energy drawn from the supply utility before the battery system is added to the community during peak tariff periods and comparing it with the same value when the battery has been added to the community (more details in the SI section S5). In addition, the smoothing capability can be determined by considering how precisely the demand follows the target. The percentage root mean square error (%RMSE) between the community power flow target and the actual community power flow is used to assess the EMS performance (calculated as shown in the SI section S6). Finally, the community self-consumption (of its locally generated PV energy) enabled by the energy storage system is also presented to demonstrate the benefits to the community as a whole (SI Section S5).

2.5. Financial and environmental analysis

The financial and environmental analysis focuses on understanding trade-offs between cost of electricity provision, renewable energy self-consumption, and life cycle greenhouse gas emissions for the 60 homes community. The parameters of the different scenarios vary as follows: the PV installation can vary from 0 to 20 houses. The total generation capacity of the community therefore varies from 0 to 77.8 kW. The battery capacity can be increase by adding two packs of 10.5 kWh in parallel at a time. The minimum size is 63kWh (Six packs in parallel) and the maximum size considered 588 kWh (26 packs) for the cases in which 20 houses are equipped with PVs. The power converter rating has also been varied from 20 kW to 80 kW (10 kW intervals). For all scenarios, export of excess electricity from the community to the grid is allowed. In total, 364 combinations of PV and ba ttery capacity are evaluated. Key scenarios highlighted in the paper are:

A. Grid only
B. 10 PV (3.89 kW PV installations at 10 houses; 38.9 kW total)
C. 20 PV (3.89 kW PV installations at 20 houses; 77.8 kW total)
D. 0 PV – 40 kW – 105 kWh (grid only + 105 kWh storage capacity and 40 kW inverter)
E. 10 PV – 50 kW – 147 kWh (10 PV case + 50 kWh storage capacity and 147 kW inverter)
F. 20 PV – 50 kW – 168 kWh (20 PV + 168 kWh storage capacity and 50 kW inverter)

2.5.1 Cost model

The cost model estimates the electricity provision cost for the scenarios A-F [50], based on wholesale electricity costs. UK-specific cost data on PV installations is used [53], assuming no economy of scale for multiple, single-house installations within the community, and operating and maintenance costs are assumed to be negligible. Installed lithium-ion battery cost data is taken from a review comparing electricity storage systems [34], accounting for the base battery cost, balance of plant (including installation, power conversion system), and fixed/variable operating and maintenance costs, and assuming that specific costs of grid-scale energy storage would be achievable at community energy storage scale. Average values from [34] are employed, and linearly scaled with the capacity considered in each scenario. As battery cost has significant uncertainty, a sensitivity analysis is developed to evaluate implications on overall results.

All costs and revenues are considered on an annual basis to determine the annual energy supply cost to the community, with upfront capital costs converted to equivalent annual costs using the capital recovery factor:

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

where *r* is the project discount rate (assumed here as 8%) and *n* is the project life, assumed to be 10 years for the PCS and 30 years for the PVs. Degradation of PV efficiency capacity over time is not considered within the models. Battery lifetime is assumed to be 3000 cycles at 80% depth of discharge or 20 year (the earliest reached), after which is considered replaced with an identical battery. This is a conservative estimate of battery life [38, 54], as values up to 30,000 cycles have been reported [30].

To test the effect that potential price variations have on the system performance, future scenarios are simulated. Forecasted prices for batteries (60% reduction) [55] and PV for 2040 (65% reduction) [56] are tested. A longer battery lifetime of 6000 cycles (as in [54]) is also considered. In detail the scenarios are described as follows:

- Original (cases presented in previous sections)
- 65% PV cost reduction (original scenario with 65% PV cost reduction)
- 65% PV & 60% battery cost reduction & 6000 cycles (same as above with battery lifetime extended to 6000 cycles)

Future scenarios do not consider improvements in the efficiency of equipment, nor changes in the UK grid mix.

2.5.2 Greenhouse gas emissions model

The calculation of GHG emissions over the full life cycle considers the generation of grid electricity, as well as the production of the PV system and the battery storage infrastructure. Upfront impacts of producing the PV generation and battery storage equipment is amortised across the project life with no discount rate applied (e.g., straight-line amortisation).

Impacts associated with grid electricity consumption are estimated based on the average grid mix. The grid electricity supply analysis is taken from the 2020 GHG reporting conversion factors [57]. The model does not consider the marginal electricity source consumed/displaced at times of electricity exchange between the grid and community. By reducing demand on grid electricity at peak times, the community energy storage system may reduce demand for high-GHG electricity generation sources (e.g., peaking natural gas turbines), while charging storage with PV-generated or lower GHG grid sources at times of low demand. We have also calculated the difference in GHG intensity between electricity input to storage and that avoided by use of stored electricity in peak times that is required to fully compensate for GHG emissions associated with the energy storage system.

For PV, only their production is considered as there are no major environmental impacts during their use-phase. The panel production emissions are calculated based on harmonised results presented in Hsu et al. [58]. GHG emissions are adapted for the study location (Nottingham, UK), with annual solar insolation of 923/m2 [59]. Similarly, GHG emissions associated with battery manufacture are extracted from a previous harmonisation study [60]. The GHG emissions are linearly scaled based on the energy storage capacity of the system (kWh). The battery emissions are annualised using their calculated lifespan (the earliest between 3000 cycles and 20 years). As a wide range of GHG impacts of battery manufacture have been reported in the literature, we undertake a sensitivity analysis of this parameter to consider its influence on results. Emissions associated with the power conversion system (PCS) are obtained from Ecoinvent 3.4 [61] and are linearly scaled based on capacity (kW). End of life management of the PV and energy storage system components are not considered in this study, as there is limited understanding of how these components will be managed at end of life.

3. Results

3.1 Energy Management Strategy – Peak Reduction

The performance of the EMS was illustrated in Figure 2 in section 2.4, where it can be clearly be seen that the EMS significantly reduces export to the grid and reduces the consumption peaks. In particular, the battery has a significant influence on reducing the energy drawn by the community during the typical period of "evening peak" consumption.

To determine the effect of the techniques used for predicting load and PV generation (section 2.2), a set of simulation scenarios were examined for a community with 10 houses, each with a PV system. Battery capacity was set at 147kWh and the power convertor was rated at 50kW. The results are shown in Table 1~~Table 1~~.

Table 1 – Prediction algorithm results

	Average Peak Energy Reduction	% RMS error
Perfect prediction	39%	6%
Autoregressive prediction	30%	7%
Persistence prediction	26%	8%

The use of an EMS with a battery storage system significantly reduces peak energy consumption (peak shaving) and the EMS also follows the reference with a good accuracy (low RMS error). The choice of prediction technique demonstrates that the two computationally simple approaches (Autoregressive and Persistence) are effective – it is questionable whether a more computationally or data intensive algorithm (based on artificial intelligence for example) would provide significant benefit as it is still unlikely to come close to perfect prediction. The approach used for the following economic analysis uses the autoregressive prediction algorithm.

Energy balance data are shown for the six key scenarios in Table 2; results for additional iterations of PV and energy storage capacity can be found in the SI (section S8). As to be expected, increasing PV capacity reduces demand on grid electricity and can result in significant electricity exports when PV generation exceeds local demand. Electricity exports account for approximately one third of PV generation when PV is installed on 20 of 60 community houses; this can be reduced to less than 10% with community energy storage available. PV generation alone is unable to appreciably reduce peak demand for grid electricity (2% to 3% reduction), due to mismatch between times of PV generation and community electricity consumption. Energy storage is thus essential to reduce grid peak demand, achieving an average reduction in peak demand of ~30%.

Table 2 – Selected cases: technical properties

	Grid import (MWh-y)	PV gen. (MWh-y)	Export (MWh-y)	Storage roundtrip efficiency (%)	Average peak demand reduction (%)
Grid only	229.1	0.0	-	-	-
10 PV	191.7	42.5	5.1	-	2%
20 PV	173.0	84.9	28.9	-	3%
0 PV - 30 kW - 84 kWh	240.32	0.0	-	76%	24%
10 PV - 50 kW - 147 kWh	202.8	42.5	0.2	74%	30%
20 PV - 50 kW - 168 kWh	169.6	84.9	8.2	76%	32%

3.2 Cost model

The capital costs associated with installing PV generation and energy storage capacity within the community are significant and result in a net increase in energy costs to supply the community despite reducing demand for grid electricity to various degrees.

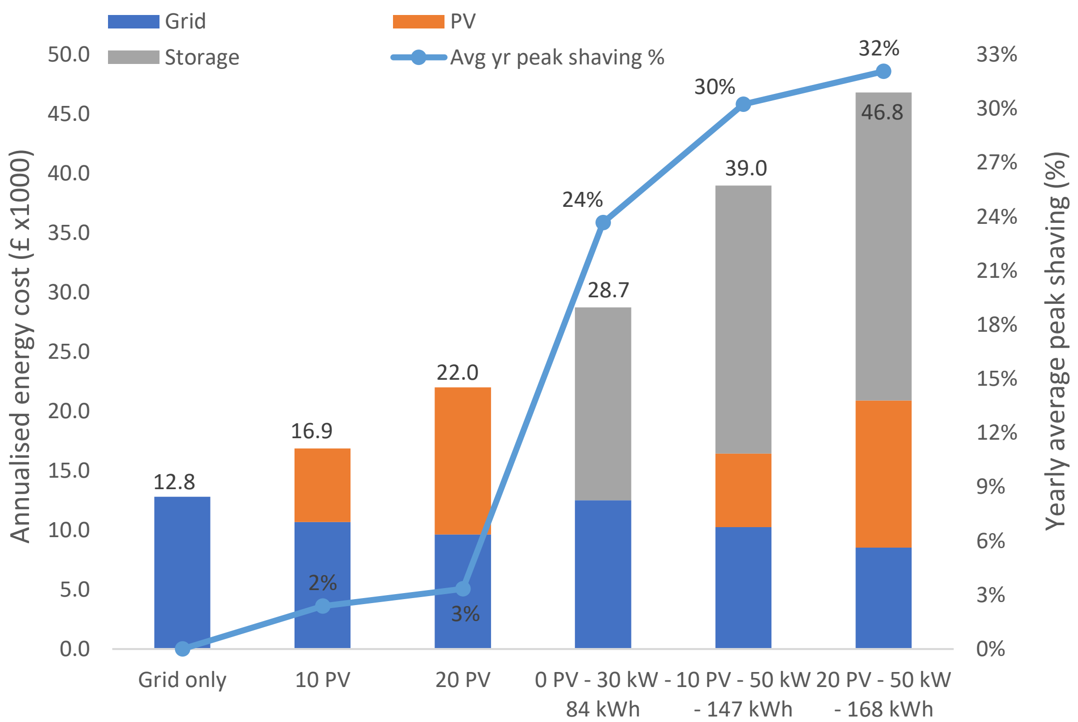

Figure 3 – Selected cases annualised cost

Results for the key scenarios are shown in Error! Reference source not found.~~Table 3~~ Error! Reference source not found. and Error! Reference source not found.~~Figure 3~~, and data for additional configurations are available in the Supporting Information.

Systems with PV generation are able to reduce demand for grid electricity by 17% (10PV scenario) and 25% (20PV scenario) (Table 2) and are able to export excess generation as a revenue source. The financial benefits of PV generation – reduced grid electricity purchases and revenues from excess generation sales at wholesale value - do not balance the upfront cost of installing PV capacity, increasing annual energy costs by 30% (10 PV case) and 70% (20 PV case).

Table 3 – Selected cases: annualised cost breakdown (grid + capital costs)

	Annualised costs (1000£)				Cost of storage (£/kWh)
	Grid	**PV**	**Storage**	**Total**	
Grid only	12.8	0.0	0.0	12.8	-
10 PV	10.7	6.2	0.0	16.9	-
20 PV	9.6	12.4	0.0	22.0	-
0 PV - 30 kW - 84 kWh	12.5	0.0	16.2	28.7	0.46
10 PV - 50 kW - 147 kWh	10.3	6.2	22.5	39.0	0.51
20 PV - 50 kW - 168 kWh	8.5	12.4	25.9	46.8	0.49

Installing energy storage capacity alone (without PV generation) reduces demand at times of high electricity cost by purchasing and storing electricity at lower cost times. Peak demand is reduced by 24%. However, due to roundtrip efficiency of the storage system, total electricity demand increases by ~10% in this case, resulting in a net reduction in the cost of grid purchases of only 3%. The small reduction in grid purchase costs is dwarfed by the cost of the energy storage system, increasing community by 124%. Scenarios with both PV and energy storage can achieve further reductions in peak electricity demand of 30% and 32% in the selected scenarios but at a further increase in supply costs of nearly 300%. Further increasing storage capacity results in rapidly increasing costs and achievement of marginal additional reduction in peak demand from the grid (see Figure S.XX in the SI). The cost of storing and delivering electricity in the community energy system evaluated here ranges from £0.43/kWh to more than £1/kWh. Costs of energy storage are unlikely to be significantly improved with larger scale energy storage (e.g., by considering larger community, or city). Costs assessed in this study assume that utility-scale specific energy storage costs ($/kWh capacity) could be achieved in community energy storage systems. Further, the specific energy storage requirement for community energy systems (kWh capacity per household) has been previously found to not decrease significantly beyond a community size of 30 households [62].

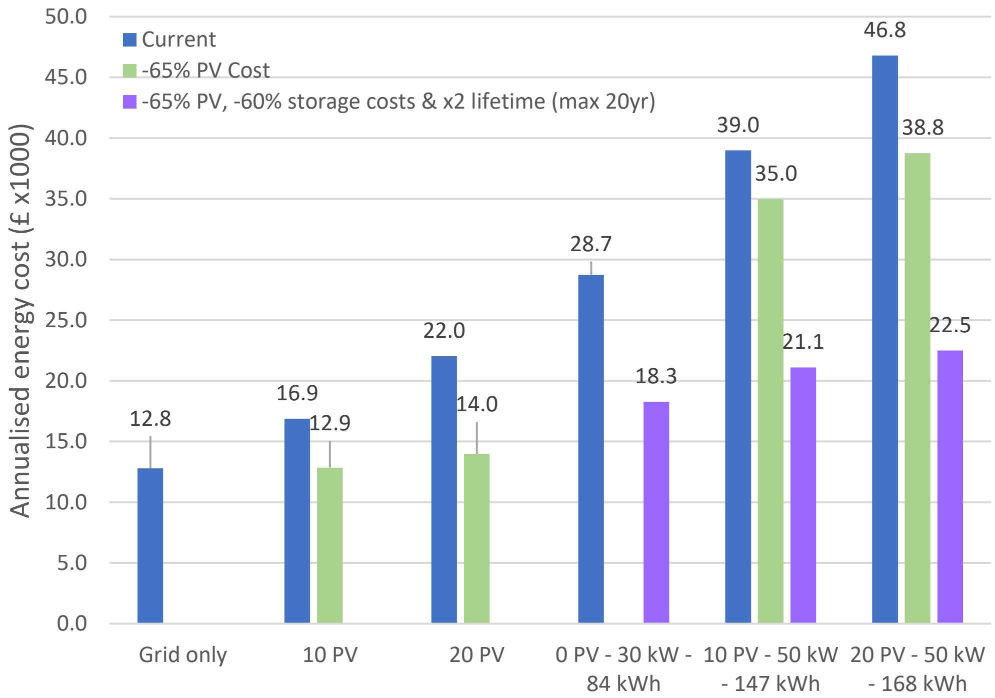

Figure 4 – Future cost projection of selected cases for the year 2040.

Expected cost reductions and lifetime improvements for the PV and energy storage systems will make community energy infrastructure more attractive for investment by 2040 with anticipated cost reductions of 65% and 60% for PV and storage costs, and doubling lifetime of battery storage systems [55,56,57] (Figure 4). All scenarios would still result in an increase in electricity cost compared to current grid retail prices (future grid electricity costs are not considered). Reducing upfront PV costs by 65% will realise a generation source that is only marginally higher than current grid electricity costs. Anticipated lower battery storage costs, and longer battery lifetimes, will still contribute to higher overall energy supply costs than the current electric grid. The cost of supplying electricity from the energy storage system decreases, to a lower range of £0.14 to £0.49 with anticipated cost reductions and extended lifetime.

3.3 GHG emissions model

Renewable electricity generation with PV is able to reduce GHG emissions associated with electricity supply to the community, whereas the energy storage system will increase GHG emissions at the community level due to the embodied emissions of the storage equipment and roundtrip efficiency losses. As shown in **Error! Reference source not found.**~~Table 4~~ and **Error! Reference source not found.**~~Figure 5~~, GHG emissions are mostly connected with electricity purchases from the current grid mix. The emissions associated with PV generation are less than grid-average GHG emissions, and so it achieves a net reduction in emissions through self-consumption or grid export, by displacing generation sources that currently supply either the community or other customers.

In contrast, scenarios with energy storage increase net GHG emissions associated with electricity supply to the community. This results from embodied GHG emissions related to the manufacture of the storage system components (battery, inverter, balance of plant), and roundtrip efficiency-related losses. Storing grid electricity to shift demand from high-cost times to lower cost times requires the purchase of a greater quantity of electricity from the grid than direct consumption. Similarly, using storage to increase self-consumption is found to increase overall GHG emissions, as roundtrip losses to store and use PV generation within the community exceed distribution losses associated with grid export.

A key limitation of the assessment approach is that it does not consider the marginal effects of a community energy store on the grid generation mix. It is plausible that the peak shaving ability provided by the energy storage system could reduce demand from the grid at times where the marginal supply would be associated with higher than average GHG emissions (e.g., due to contribution of peaking power plants, or greater reliance on fossil fuel-fired generators). The additional GHG emissions burden of the energy storage system, approximately 70 $gCO_2eq./kWh$ supplied from battery for the key scenarios, ranges from 67 to 106 $gCO_2eq./kWh$ across all iterations. To put this in context, GHG emissions associated with relatively high efficiency natural gas combined cycle generation facilities is approximately 500 $gCO_2eq./kWh$ [63], whereas single cycle peaking gas turbines would be expected to have substantially higher emissions. If electricity stored in batteries comes from a low GHG-intensity mix, and peak shaving is able to avoid fossil fuel-fired generation, it is plausible that overall GHG emissions will be reduced overall. This is not considered in the present results. The anticipated increase in battery lifetime in future will reduce associated GHG emissions of electricity storage to a range of 30 to 106 $gCO_2eq./kWh$ delivered from the energy storage system, making a net reduction in GHG emissions more likely. The high end of the range is the same as the lifespan of large batteries is not extended by the increased cycling capability.

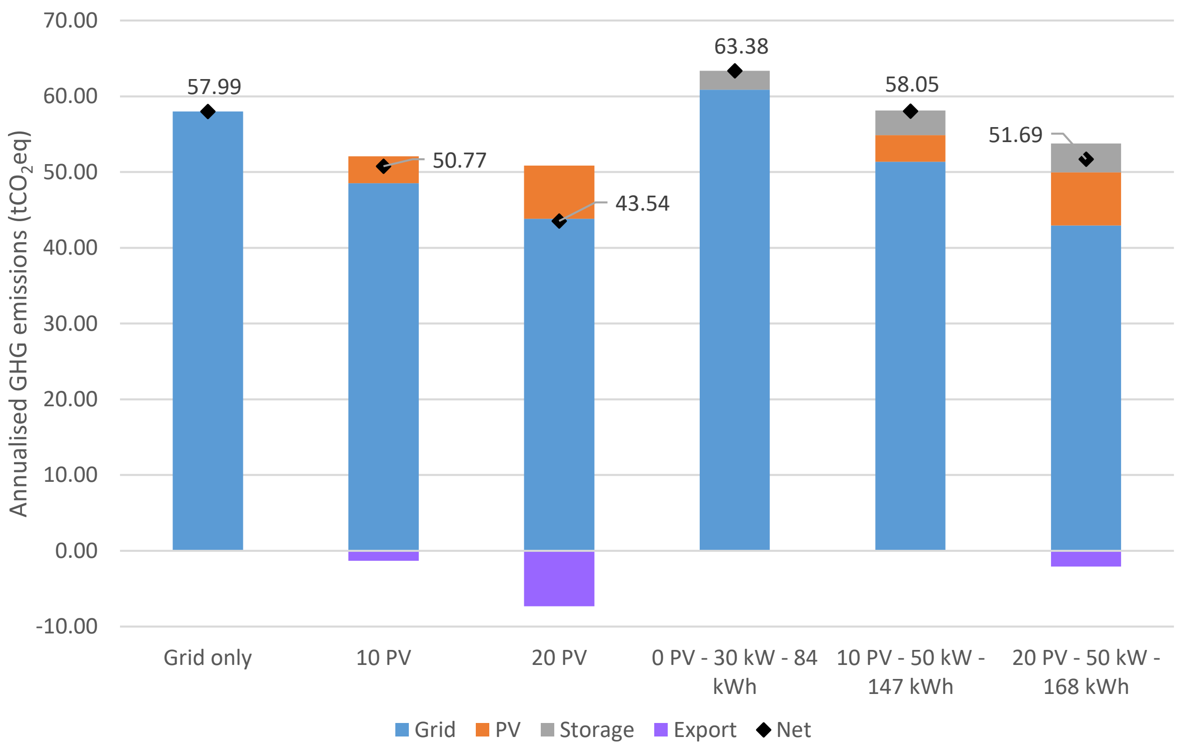

Figure 5 – Selected cases annualised GHG emissions

Table 4 – Selected cases: annualised GHG emissions breakdown

	Annual GHG emissions (tCO2eq./yr)					Additional emissions from storage (gCO_2eq/kWh)
	Grid	**PV**	**Storage**	**Export**	**Net**	
Grid only	57.99	-	-	-	57.99	-
10 PV	48.54	3.52	-	-1.30	50.77	-
20 PV	43.81	7.05	-	-7.32	43.54	-
0 PV - 30 kW - 84 kWh	60.85	-	2.53	-	63.38	71
10 PV - 50 kW - 147 kWh	51.34	3.52	3.24	-0.05	58.05	73
20 PV - 50 kW - 168 kWh	42.93	7.05	3.79	-2.09	51.69	71

This is a delicate balance as to an increase in renewable generation/storage could be associated a drop in efficiency of gas turbines forced shutdown/start-up more often or even to run at a lower percentage of load. Gas turbines operating at 50% of their nominal load could suffer a drop in efficiency up to 70% [64]. It then becomes essential that storage is charged only with renewable energies and that electricity generation with gas turbines is made more efficient, for example by using a larger number of smaller turbines, or that more flexible technologies are used like a few internal combustion engines running in parallel that can be turned on and off when needed [65], or a combination of the two.

4. Discussion and conclusions

This study has proposed a robust and effective energy management strategy and tested it over a year of data under different operational conditions. It can achieve up to 40% peak reduction with perfect prediction of consumption and generation variables, and 32% with the autoregressive forecasting techniques. The limit of this type of approach, using real time prices as a proxy to identify the grid consumption peaks, is that when real time prices are not varying with the peak demand, peak shaving does not occur. An algorithm that keeps track of both prices and real time demand could be a solution, but this is material for further studies that might also include battery degradation and seasonal storage. Further studies could also investigate the benefits brought by the peak shaving such as the reduction of distribution network losses. As losses reduce as the square of peak power, this improved efficiency might bring benefits in terms of costs and emissions.

In this paper we have also shown that trade-offs exist between electricity supply costs, peak reduction and life cycle GHG reductions. PV generation provides a significant reduction in GHG emissions, but makes little contribution to reducing peak demand from the grid. Community energy storage in batteries are effective at reducing peak demand, but at significant additional costs, and may result in a modest increase in GHG emissions due to emissions associated with battery manufacture. GHG emissions reductions with community-level energy storage would be possible, provided that they are charged with renewable (or low carbon) electricity sources and discharged at times where fossil fuel generation can thereby be avoided, but analysis of such a management strategy is outside of the scope of the current paper. Anticipated cost reductions for PV and battery, and longer battery cycle life, will considerably reduce the cost of community electricity generation and storage for managing peak grid demand. There are additional opportunities in future distribution systems for revenue which are not currently available, and these should be briefly mentioned.

1) System losses
   Losses in the distribution system are proportional to the square of the load current. This means that if the peak power demands double, the system losses will quadruple. If consumption peaks can be reduced using energy storage (or at least maintained at a reasonable limit as the electrification of heating and transport increases overall electricity demand), then it should be possible to quantify savings if these additional system losses are not incurred.
2) Deferment of Infrastructure Upgrade
   As mentioned in (1), domestic and commercial electricity loads will increase significantly over coming years with the move towards, for example, electric vehicles and heat pump technologies. Increasing loads can potentially overload existing infrastructure – cables, switchgear and transformers. Energy storage can help to defer any infrastructure upgrades. DNOs can potentially reward customers who invest in energy storage technology if it can reduce the immediate requirements for infrastructure overhaul.
3) Additional benefits for System Power Quality
   The power convertors used to interface energy storage to the grid can provide additional benefits to power quality. For example, voltage levels may potentially change quite drastically in future

distributions levels as they will be high during times of high generation (midday on sunny days) and low in the evenings when there is high load (cooking, charging EV). Power convertors can inject reactive power at relatively low operational cost to mitigate these swings. Again reward could be offered for this functionality.

4) "Go Green"
Energy storage technology at all levels of the grid is an essential part of moving to a smarter more sustainable electricity system. The cost of investing in energy storage technology could be considered as a necessary cost for "going green".

It is clear that additional reward should be obtained if these system level benefits can be provided by electricity prosumers. The advantages of working within a community are that the cost of energy storage infrastructure can be reduced per customer. The large load variations created by one household are largely smoothed when a community of over 30 is considered [62], leading to a significant reduction of energy storage capacity per household (from 6kWh to 3kWh). The concepts of Distribution System Operators (DSO) and Energy Service Companies (ESCo) are moving the idea of Community Energy forward [66].

Acknowledgements
This work was supported by the UK Engineering and Physical Research Council (EPSRC) through the Intelligent MicroGrids with Appropriate Storage for Energy (IMASE) project [grant number EP/K036297/1] and the Realising Energy Storage Technologies in Low-carbon Energy Systems (RESTLESS) project [grant number EP/N001893/1] part of the EPSRC Energy Superstore Hub and is associated with the UK Energy Research Centre (UKERC).

References

1. United Nations. *The Paris agreement*. 2015 [cited 2021 28/02]; Available from: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.
2. Department of Energy and Climate Change. *UK Renewable Energy Roadmap Update 2013*. 2013 04/2018]; Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/255182/UK_Renewable_Energy_Roadmap_-_5_November_-_FINAL_DOCUMENT_FOR_PUBLICATIO___.pdf.
3. Comittee on Climate Change, *The 5th Carbon Budget*. 2015.
4. Department for Business Energy & Industrial Strategy and The Rt Hon Chris Skidmore MP. *UK becomes first major economy to pass net zero emissions law* 2019 [cited 2020 20/03]; Available from: https://www.gov.uk/government/news/uk-becomes-first-major-economy-to-pass-net-zero-emissions-law.
5. Department for Business Energy & Industrial Strategy. *Energy Trends: UK renewables*. 2020 12/2020]; Available from: https://www.gov.uk/government/statistics/energy-trends-section-6-renewables.
6. Munshi, P.U., J. Pichel, and E.S. Kwei, *Energy Storage: Game-changing Component of the Future Grid*. 2009, Piper Jaffray Investment Research,.
7. Mammoli, A., et al. *Using high-speed demand response of building HVAC systems to smooth cloud-driven intermittency of distributed solar photovoltaic generation*. in *PES T&D 2012*. 2012.
8. Denholm, P., et al., *The Role of Energy Storage with Renewable Electricity Generation*. 2010, National Renewable Energy Laboratory (NREL).
9. Durand, J.-M., M. João Duarte, and P. Clerens, *Joint EASE/EERA recommendations for a European Energy Storage Technology Development Roadmap towards 2030*. 2013, EASE/EERA.
10. Vieira, F.M., P.S. Moura, and A.T. de Almeida, *Energy storage system for self-consumption of photovoltaic energy in residential zero energy buildings.* Renewable Energy, 2017. **103**: p. 308-320.
11. Luthander, R., et al., *Self-consumption enhancement and peak shaving of residential photovoltaics using storage and curtailment.* Energy, 2016. **112**: p. 221-231.
12. Luthander, R., et al., *Photovoltaic self-consumption in buildings: A review.* Applied Energy, 2015. **142**: p. 80-94.
13. Moshövel, J., et al., *Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption.* Applied Energy, 2015. **137**: p. 567-575.
14. KONG, X., et al., *Day-ahead optimal scheduling method for grid-connected microgrid based on energy storage control strategy.* Journal of Modern Power Systems and Clean Energy, 2016. **4**(4): p. 648-658.
15. Ranaweera, I. and O.-M. Midtgård, *Optimization of operational cost for a grid-supporting PV system with battery storage.* Renewable Energy, 2016. **88**: p. 262-272.
16. Zhang, L. and Y. Li. *Optimal energy management of hybrid power system with two-scale dynamic programming*. in *2011 IEEE/PES Power Systems Conference and Exposition*. 2011.
17. Hanna, R., et al., *Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting.* Solar Energy, 2014. **103**: p. 269-287.
18. Jiang, Q., M. Xue, and G. Geng, *Energy Management of Microgrid in Grid-Connected and Stand-Alone Modes.* IEEE Transactions on Power Systems, 2013. **28**(3): p. 3380-3389.
19. Zhang, Y., et al., *An intelligent control strategy of battery energy storage system for microgrid energy management under forecast uncertainties.* Int. J. Electrochem. Sci, 2014. **9**: p. 4190-4204.

20. Parisio, A., et al., *Use of model predictive control for experimental microgrid optimization.* Applied Energy, 2014. **115**: p. 37-46.
21. Malysz, P., S. Sirouspour, and A. Emadi, *An Optimal Energy Storage Control Strategy for Grid-connected Microgrids.* IEEE Transactions on Smart Grid, 2014. **5**(4): p. 1785-1796.
22. Kim, S.K., et al., *Dynamic Modeling and Control of a Grid-Connected Hybrid Generation System With Versatile Power Transfer.* IEEE Transactions on Industrial Electronics, 2008. **55**(4): p. 1677-1688.
23. Zhou, H., et al., *Composite Energy Storage System Involving Battery and Ultracapacitor With Dynamic Energy Management in Microgrid Applications.* IEEE Transactions on Power Electronics, 2011. **26**(3): p. 923-930.
24. Pascual, J., et al., *Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting.* Applied Energy, 2015. **158**: p. 12-25.
25. Wan Alwi, S.R., et al., *New graphical tools for process changes via load shifting for hybrid power systems based on Power Pinch Analysis.* Clean Technologies and Environmental Policy, 2013. **15**(3): p. 459-472.
26. Mohammad Rozali, N.E., et al., *Peak-off-peak load shifting for hybrid power systems based on Power Pinch Analysis.* Energy, 2015. **90**: p. 128-136.
27. Giaouris, D., et al., *Power grand composite curves shaping for adaptive energy management of hybrid microgrids.* Renewable Energy, 2016. **95**: p. 433-448.
28. Jülch, V., *Comparison of electricity storage options using levelized cost of storage (LCOS) method.* Applied Energy, 2016. **183**: p. 1594-1606.
29. Obi, M., et al., *Calculation of levelized costs of electricity for various electrical energy storage systems.* Renewable and Sustainable Energy Reviews, 2017. **67**: p. 908-920.
30. Battke, B., et al., *A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications.* Renewable and Sustainable Energy Reviews, 2013. **25**: p. 240-250.
31. Cucchiella, F., I. D'Adamo, and M. Gastaldi, *Photovoltaic energy systems with battery storage for residential areas: an economic analysis.* Journal of Cleaner Production, 2016. **131**: p. 460-474.
32. Lai, C.S. and M.D. McCulloch, *Levelized cost of electricity for solar photovoltaic and electrical energy storage.* Applied Energy, 2017. **190**: p. 191-203.
33. Linssen, J., P. Stenzel, and J. Fleer, *Techno-economic analysis of photovoltaic battery systems and the influence of different consumer load profiles.* Applied Energy, 2017. **185**: p. 2019-2025.
34. Zakeri, B. and S. Syri, *Electrical energy storage systems: A comparative life cycle cost analysis.* Renewable and Sustainable Energy Reviews, 2015. **42**: p. 569-596.
35. Uddin, K., et al., *Techno-economic analysis of the viability of residential photovoltaic systems using lithium-ion batteries for energy storage in the United Kingdom.* Applied Energy, 2017. **206**(Supplement C): p. 12-21.
36. Merei, G., et al., *Optimization of self-consumption and techno-economic analysis of PV-battery systems in commercial applications.* Applied Energy, 2016. **168**: p. 171-178.
37. Hoppmann, J., et al., *The economic viability of battery storage for residential solar photovoltaic systems – A review and a simulation model.* Renewable and Sustainable Energy Reviews, 2014. **39**: p. 1101-1118.
38. Hesse, H., et al., *Economic Optimization of Component Sizing for Residential Battery Storage Systems.* Energies, 2017. **10**(7): p. 835.
39. Jacob, A.S., R. Banerjee, and P.C. Ghosh, *Sizing of hybrid energy storage system for a PV based microgrid through design space approach.* Applied Energy, 2018. **212**: p. 640-653.
40. Santos, J.M., P.S. Moura, and A.T.d. Almeida, *Technical and economic impact of residential electricity storage at local and grid level for Portugal.* Applied Energy, 2014. **128**: p. 254-264.
41. TENG, F. and G. STRBAC, *Business cases for energy storage with multiple service provision.* Journal of Modern Power Systems and Clean Energy, 2016. **4**(4): p. 615-625.

42. Nugent, D. and B.K. Sovacool, *Assessing the lifecycle greenhouse gas emissions from solar PV and wind energy: A critical meta-survey.* Energy Policy, 2014. **65**: p. 229-244.
43. Gerbinet, S., S. Belboom, and A. Léonard, *Life Cycle Analysis (LCA) of photovoltaic panels: A review.* Renewable and Sustainable Energy Reviews, 2014. **38**: p. 747-753.
44. Hiremath, M., K. Derendorf, and T. Vogt, *Comparative Life Cycle Assessment of Battery Storage Systems for Stationary Applications.* Environmental Science & Technology, 2015. **49**(8): p. 4825-4833.
45. Parra, D., et al., *An interdisciplinary review of energy storage for communities: Challenges and perspectives.* Renewable and Sustainable Energy Reviews, 2017. **79**: p. 730-749.
46. Abdon, A., et al., *Techno-economic and environmental assessment of stationary electricity storage technologies for different time scales.* Energy, 2017. **139**: p. 1173-1187.
47. Dong, S., et al., *Techno-enviro-economic assessment of household and community energy storage in the UK.* Energy Conversion and Management, 2020. **205**: p. 112330.
48. Campbell, P.R. and K. Adamson. *Methodologies for load forecasting*. in *2006 3rd International IEEE Conference Intelligent Systems*. 2006. IEEE.
49. Chaturvedi, D., S.A. Premdayal, and A. Chandiok, *Short Term Load Forecasting using Neuro-fuzzy-Wavelet Approach.* International Journal of Computing Academic Research (IJCAR), 2013. **2**(1): p. 36-48.
50. Elexon Ltd. *The New Electricity Trading Arrangements for the Imbalance Market in UK 2011*. Available from: https://www.bmreports.com/bmrs/?q=balancing/detailprices.
51. Richardson, I. and M. Thomson, *One-Minute Resolution Domestic Electricity Use Data, 2008-2009*, in *Colch. Essex UK Data Arch*. 2010.
52. IEEE Standards Association, *Guide for the Characterization and Evaluation of Lithium-Based Batteries in Stationary Applications*. 2017.
53. Department for Business Energy & Industrial Strategy. *Solar PV cost data*. 2017 08/2017]; Available from: https://www.gov.uk/government/statistics/solar-pv-cost-data.
54. Barnhart, C.J. and S.M. Benson, *On the importance of reducing the energetic and material demands of electrical energy storage.* Energy & Environmental Science, 2013. **6**(4): p. 1083-1092.
55. Schmidt, O., et al., *The future cost of electrical energy storage based on experience rates.* Nature Energy, 2017. **2**: p. 17110.
56. Mayer, J., et al., *Current and Future Cost of Photovoltaics*. 2015.
57. Department for Business Energy & Industrial Strategy. *Government emission conversion factors for greenhouse gas company reporting - Collection*. 2020 [cited 2020 12]; Available from: https://www.gov.uk/government/collections/government-conversion-factors-for-company-reporting.
58. Hsu, D.D., et al., *Life Cycle Greenhouse Gas Emissions of Crystalline Silicon Photovoltaic Electricity Generation.* Journal of Industrial Ecology, 2012. **16**: p. S122-S135.
59. Natural Resources Canada. *RETScreen Expert* 2017; Available from: http://www.nrcan.gc.ca/energy/software-tools/7465.
60. Peters, J.F. and M. Weil, *Providing a common base for life cycle assessments of Li-Ion batteries.* Journal of Cleaner Production, 2018. **171**(Supplement C): p. 704-713.
61. Ecoinvent. *Ecoinvent Database 3.4*. 2017; Available from: https://www.ecoinvent.org/.
62. Fazeli, A., et al. *Investigating the impact of varying the number of distributed energy resources on controlling the power flow within a microgrid*. in *2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. 2015. IEEE.
63. Bruckner, T., et al. *Energy systems*. 2014; Available from: https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_chapter7.pdf.
64. Wartsila. *Combustion Engine vs. Gas Turbine: Part Load Efficiency and Flexibility*. [cited 2021 26/09]; Available from: https://www.wartsila.com/energy/learn-more/technical-comparisons/combustion-engine-vs-gas-turbine-part-load-efficiency-and-flexibility.

65. Wartsila, M.R.-. *The Flexibility of Internal Combustion Engines*. 2014; Available from: https://www.power-eng.com/renewables/the-flexibility-of-internal-combustion-engines/#gref.
66. Community energy England. [cited 2021 11/04]; Available from: https://communityenergyengland.org/.