

Revenue stacking for behind the meter battery storage in energy and ancillary services markets

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ABSTRACT

Several sources of revenue are available for battery storage systems that can be stacked to further increase revenue. Typically, price arbitrage is used to gain revenue from battery storage. However, additional revenue can be gained from participation in ancillary services such as frequency response. This study presents a linear optimisation approach to account for local energy system participation in the wholesale day-ahead electricity market and multiple frequency response services. The methodology was applied to a school case study. A breakdown of market revenue and value of investment is presented for five operating strategies. The value of availability revenue and response energy revenue are distinguished for frequency response services. Finally, the impact of revenue stacking on battery degradation is assessed. The results show that local energy systems can decrease their operating costs and improve battery storage investment viability by stacking multiple revenues, whilst reducing degradation and increasing lifetime.

1. Introduction

High penetrations of intermittent renewable generation will require flexibility from energy storage to reduce energy curtailment and reduce whole system electricity costs [1]. Energy storage systems are a key enabler of the transition to low-carbon energy systems. Energy storage supports the grid by decoupling the link between supply and demand, allowing the efficient consumption of renewable power generation and providing services to improve the security of power supply. National Grid ESO expects battery storage to increase on a domestic scale and be the leading large-scale energy storage technology, in the UK [2]. By 2050, UK grid and domestic scale battery storage must be over 110 GW to reach net zero greenhouse gas emissions [3].

Local energy systems (LESs) are collections of (flexible) energy demand, supply and/or storage that are operated to benefit local stakeholders. LESs with battery storage systems (BSSs) have several markets available to participate in to gain revenue. Participating in multiple markets to increase revenue is called 'revenue stacking'. The most common source of revenue for BSSs is purchasing electricity when the price is low and selling it (or consume it) when the price is high, called 'price arbitrage' [4]. Alternative sources of revenue are available for providing flexibility services to transmission system operators, called 'Ancillary Service'. These include frequency response, reserve and peak

demand management [5,6]. Revenue stacking raises challenges such as maximising battery revenue across multiple markets, increasing battery investment viability, and understanding the impact of market participation on the lifetime of a BSS.

Despite the significant fall in battery prices since 2010 [7], the high investment cost is still the main barrier to large scale integration of BSSs [8]. For many cases, the investment in BSSs cannot be justified for a single application. In [9], the feasibility of a BSS alongside a renewable energy park is assessed, based on price arbitrage alone. The results show the BSS is not economically feasible with current battery capital costs. In [10], the optimal configuration of the case study local energy system does not include a battery storage system. The battery was not viable for price arbitrage due to the high investment cost. This result is similar to other studies in the literature [11]. These studies show it is not profitable to invest in battery storage for price arbitrage only.

In [12], battery storage technologies are reviewed, covering their performance, system design and operation in specific applications. The study suggested that stacking of multiple revenue streams will be a vital part of integrating BSSs into future power grids. In [13], several single applications were assessed for their investment attractiveness, including arbitrage, self-consumption, investment deferral, frequency regulation and reserve. The study found that no single application was likely to be an attractive investment. Likewise, [14] studied several virtual power

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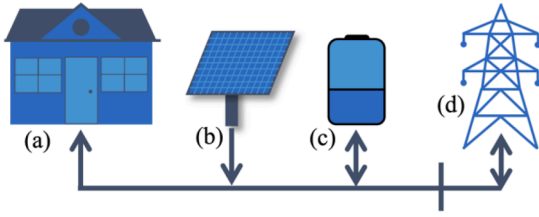


Fig. 1. Power flow diagram of local energy system configuration. The components are: (a) local demand, (b) PV generation, (c) battery storage system and (d) bidirectional connection to the grid.

plant configurations participating in frequency response services. None of the virtual power plant configurations were profitable while participating in frequency response. Analysis in [13] combined arbitrage, self-consumption and investment deferral with grid support services. Stacking two revenue streams improved investment attractiveness for all combinations of applications. In some cases, making the investment profitable. These studies have shown the need for multiple revenue streams to make battery storage financially viable. However, they do not provide adaptable methodologies to allow battery owners to maximise revenue in real markets.

In [8], multiple revenue streams were stacked and the net present value (NPV) determined. The results show higher NPVs for stacked revenues, where three revenue streams resulted in the highest NPV. As well as improving the investment prospect of BSSs, their participation in services can lead to improved safety, reliability and quality of the grid [15].

These studies provide valuable insights into the operating behaviour of BSSs and their participation in price arbitrage and ancillary services. However, a concise methodology is required for LESs with a BSS to determine their optimal operating strategy. Additionally, the contrast between availability revenue and response energy revenue from delivering the service has not been suitably explored. Finally, an understanding of the effect of revenue stacking on battery charge/discharge behaviour and its impact on battery degradation and lifetime is necessary.

This study aims to deliver a methodology suitable for LESs to determine their optimal operating strategy within GB electricity and ancillary services markets. Additionally, to demonstrate the benefit of revenue stacking for BSS operators while considering the impact on battery degradation. Therefore, this paper presents:

- A linear optimisation model to minimise LES operating cost incorporating stacking of revenues from participating in the wholesale day-ahead electricity market and frequency response services.
- A detailed breakdown of revenue from frequency response services, including both availability and dispatch revenue.
- The impact of wholesale energy market price arbitrage and stacking frequency response services on battery degradation and lifetime.

The remainder of this paper is structured as follows: Section II describes the methodology for the operational optimisation, the revenue gained from delivering a service and the evaluation of battery degradation. Section III set outs the parameters of the case study and Section IV presents the results from the modelling, providing insights into the significance of the outcomes. Finally, Section V presents the conclusion of the study.

2. Methodology

The LES configuration in this paper considers local demand, renewable generation, a BSS and a connection to the grid that allows bidirectional flow of electricity. This structure is presented in Fig. 1. The wholesale day-ahead electricity market and frequency response services

Table 1
Frequency response characteristics [17].

Characteristic	DC	FFRL	FFRH
Minimum power capacity (MW)	1	1	1
Availability window (block) duration (h)	24	4	4
Delivery duration, T^{FR} (hours)	0.25	0.5	0.5
Response time (s)	1	2	2

were considered in this study. In GB, National Grid ESO organise frequency response services to ensure security of electricity supply by keeping the power system frequency at 50 Hz. Frequency response services inject/absorb energy to/from the grid when the power system frequency is low ('under-frequency' event) or high ('over-frequency' event). Although several frequency response services are available, Dynamic Containment (DC) and Firm Frequency Response (FFR) were considered in this study. These were chosen due to their technical requirements being suitable for battery storage, real tenders being won by battery storage and their freedom to be stacked with price arbitrage. FFR was split into FFR low (FFRL) and FFR high (FFRH) The details of these services are summarised in Table 1. DC, FFRL and FFRH are procured 24/7, 365 days a year. The dispatch requirements provide details of when the services are dispatched into the power system. There are other ancillary services that support the power system in different ways, for more information on these and frequency response services, refer to [5, 6,16].

At the time of writing, National Grid ESO only procure DC for low frequency. Therefore, for DC and FFRL, power capacity is made available for dispatch in response to low power system frequency. DC is procured for 24 h blocks, therefore when participants bids are accepted their power capacity must be available for 24 h. Whereas Firm Frequency Response services are procured for 4 h blocks, see [17]. FFRH is identical to FFRL, except it is dispatched in response to high power system frequency. Current regulation prevents DC from being stacked with other frequency response services. Whereas FFRH and FFRL can be stacked to increase revenue. Regulation also impacts the market entry assessment process and testing requirements. DC has stringent performance testing to gain entry to the market, whereas FFRH and FFRL are more relaxed.

As shown in Table 1, the duration of delivery at full power is 15 min

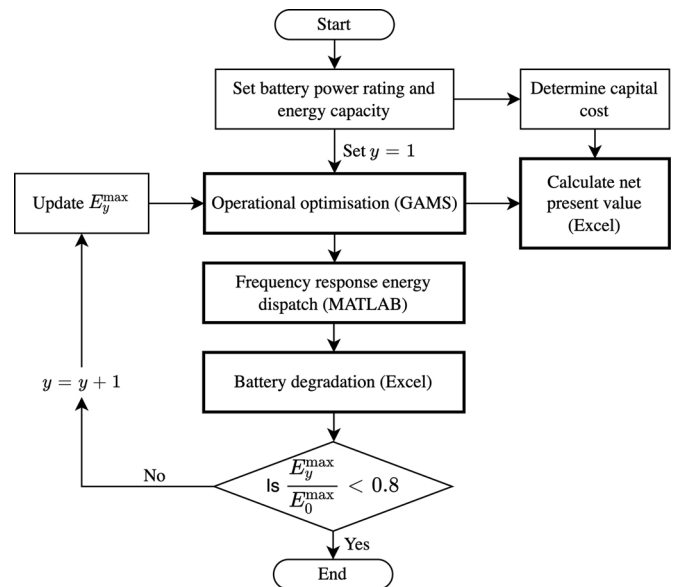


Fig. 2. Flow chart visualising the modelling process. Each block represents an independent action. The start block is first and each arrow moves to a subsequent action. Each model is highlighted with a thick outline.

Table 2
Size of t and b sets.

Service	T	B
FFRH & FFRL	4	2190
DC	24	365

for DC and 30 min for FFRH and FFRL. This determines the stored energy required for a specific committed power capacity. Furthermore, the dispatch requirements of DC, FFRH and FFRL are distinct from one another, discussed in Section II.B.

Frequency response providers are paid per hour for power capacity, called the ‘availability fee’ with unit £/kW per hour. Providers can also be paid for the energy they deliver to the grid. This is determined by the energy delivered and the balancing price and is called the ‘response energy payment’. To account for the availability fee, response energy payment, battery investment and battery degradation, the modelling was split into the following sections: day-ahead operational optimisation, NPV, service dispatch and degradation.

Each section of the methodology was modelled separately and run independently. The operational optimisation was created in GAMS. The outputs of this were imported into MATLAB, where the frequency response energy dispatch model was carried out. The operation and energy dispatch results were imported to Excel, where the battery degradation model was executed. Finally, for each iteration of y , the results of the operational optimisation were imported to Excel, where the NPV was performed. An overview of the modelling framework is shown in Fig. 2.

2.1. Operational optimisation

In the operational optimisation model the LES schedules the charging/discharging of the battery to minimise operating cost. The LES reduces operating cost by performing price arbitrage in the wholesale day-ahead electricity market and by offering frequency response services. Both the day-ahead electricity market and frequency response market prices are exogenous. Therefore, the LES is a price taker with no influence over market prices. The operational optimisation considers availability revenue but does not account for response energy revenue from frequency response. To understand the impact of this assumption, a methodology for analysing response energy revenue is presented in Section II.B. The LES gains availability revenue by making power capacity available and committing it to frequency response. Throughout the operational optimisation DC and FFRL are referred to as frequency response low (superscript FR,l) and FFRH is referred to as frequency response high (superscript FR,h).The objective function is defined as follows.

$$\text{Min } \Pi = \sum_{b=1}^B \sum_{t=1}^T \tau \left(K_{b,t}^w (P_{b,t}^{im} - P_{b,t}^{ex}) - K_b^{FR,l} P_b^{FR,l} - K_b^{FR,h} P_b^{FR,h} + K_{b,t}^{DUoS} P_{b,t}^{im} \right) \quad (1)$$

The objective function (1) minimises the LES operating cost. The operating cost is made up of the cost of importing electricity ($K_{b,t}^w P_{b,t}^{im}$), the income from exporting electricity ($K_{b,t}^w P_{b,t}^{ex}$), the availability income of frequency response low and high ($P_b^{FR,l} K_b^{FR,l}$, $P_b^{FR,h} K_b^{FR,h}$) and the cost of distribution use of system (DUoS) charges ($K_{b,t}^{DUoS} P_{b,t}^{im}$).

Table 2 shows the size of sets t and b for FFR and DC. Set b represents the blocks that frequency response services can be procured for ($b = 1, 2, \dots, B$). As shown in Table 2, the block duration for DC is 24 h and the block duration for FFRH and FFRL is 4 h. Set t represents each time step within a block ($t = 1, 2, \dots, T$).

As DC and FFR services cannot be stacked, their operational optimisations were formulated in separate models with different blocks and time steps. The wholesale day-ahead electricity price and DUoS charges change for each time step, therefore must include sets b and t . Frequency

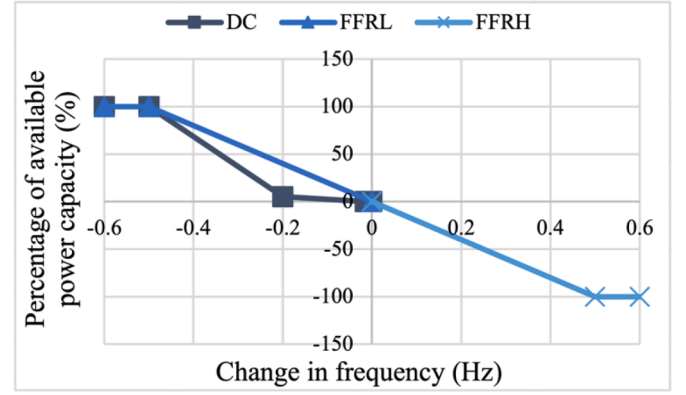


Fig. 3. Fraction of power capacity dispatched in response to change in frequency. Response requirements are shown for DC, FFRL and FFRH.

response prices are fixed for each block, therefore only require set b . Multiplying power values by the time interval (τ) converts them to energy. The optimisation was subject to the following power balance constraint.

$$P_{b,t}^{im} + P_{b,t}^{Ren} + P_{b,t}^{dis} - P_{b,t}^{ch} - P_{b,t}^{LD} - P_{b,t}^{ex} = 0 \quad (2)$$

Eq. (2) ensures that the local demand ($P_{b,t}^{LD}$) is met by the renewable generation ($P_{b,t}^{Ren}$), the import power ($P_{b,t}^{im}$) and the battery discharge ($P_{b,t}^{dis}$) and that any excess power charges ($P_{b,t}^{ch}$) the battery or is exported ($P_{b,t}^{ex}$) to the grid. The battery operating constraints are defined in (3) – (6).

$$E_{b,t} = E_{b,t=1}^{ini} + E_{b,t-1|t>1} + E_{b-1,T|b>1,t=1} + \tau \left(\eta^{ch} P_{b,t}^{ch} - \frac{P_{b,t}^{dis}}{\eta^{dis}} \right) \quad (3)$$

$$0 + P_b^{FFRL} T^{FR} \leq E_{b,t} \leq E_y^{max} - P_b^{FFRH} T^{FR} \quad (4a)$$

$$0 + P_b^{DC} T^{FR} \leq E_{b,t} \leq E_y^{max} \quad (4b)$$

$$0 \leq P_{b,t}^{ch} + P_b^{FR,h} \leq P^{max} \quad (5)$$

$$0 \leq P_{b,t}^{dis} + P_b^{FR,l} \leq P^{max} \quad (6)$$

Eq. (3) determines the energy in the battery ($E_{b,t}$), which depends on the energy in the previous time step and the charging/discharging power ($P_{b,t}^{ch}$, $P_{b,t}^{dis}$). Battery energy in the previous time step was defined using three terms: the initial energy ($E_{b=1,t=1}^{ini}$), the previous energy within a block ($E_{b,t-1|t>1}$) and the energy in the last time step from the previous block ($E_{b-1,T|b>1,t=1}$). Eq. (4a) is the energy stored in the battery for the FFR services, where $E_{b,t}$ is limited to the battery capacity (E_y^{max}) minus the energy deficit required to deliver the FFR high service ($P_b^{FFRH} T^{FR}$). Additionally, the minimum energy stored is limited to the energy required to deliver the FFR low service ($P_b^{FFRL} T^{FR}$). T^{FR} is the duration of frequency response delivery and is defined in Table 1. Eq. (4b) is the equivalent of (4a) but for DC. FFR and DC were formulated in separate optimisations due to different block durations. With equal block durations, a single optimisation can be formulated. The committed power (P_b^{FFRH} , P_b^{FFRL} , P_b^{DC}) can be limited to zero to analyse various combinations of services. Eqs. (5) and (6) ensure enough power capacity is available to deliver the frequency response service. The charging/discharging power plus the power committed to frequency response ($P_b^{FR,h}$, $P_b^{FR,l}$) must be within the battery power rating (P^{max}). The optimisation is a linear programming problem, which was formulated in GAMS and solved with GUROBI.

2.2. Frequency response energy dispatch

As well as payments for availability, some frequency response services also provide payments for energy delivered to the grid, called the ‘response energy payment’ (£/MWh) [17]. Participants of DC are only paid an availability fee [18], whereas FFR received an availability fee and response energy payment. The frequency response energy dispatch model utilised power system frequency data to determine the energy dispatched in each time step. National Grid ESO publish GB power system frequency measurements in time intervals of 1 s [19]. Additionally, National Grid ESO publish the dynamic dispatch requirements for DC and FFR [17], which are shown in Fig. 3.

Fig. 3 shows the fraction of committed power capacity that must be dispatched for specific changes in frequency. For both DC and FFRL, when the change in frequency is negative (frequency falls below 50 Hz) there is a positive power capacity response. For FFRH, when a positive change in frequency occurs (frequency goes above 50 Hz) there is a negative power capacity response. The dispatch requirements shown in Fig. 3 are written as:

$$P_{b,t,s}^{DC,\%} = \begin{cases} 100, \Delta f_s \leq -0.5 \\ -316.7\Delta f_s - 58.3, -0.5 < \Delta f_s \leq -0.2 \\ -27.0\Delta f_s - 0.4, -0.2 < \Delta f_s \leq -0.015 \\ 0, \Delta f_s > -0.015 \end{cases} \quad (7)$$

$$P_{b,t,s}^{FFRL,\%} = \begin{cases} 100, \Delta f_s \leq -0.5 \\ -200\Delta f_s, -0.5 < \Delta f_s < 0 \end{cases} \quad (8)$$

$$P_{b,t,s}^{FFRH,\%} = \begin{cases} -200\Delta f_s, 0 < \Delta f_s < 0.5 \\ -100, \Delta f_s \geq 0.5 \end{cases} \quad (9)$$

The resulting percentage power capacity values for each second of the year were transformed into energy dispatched in each time step using (10).

$$E_{b,t}^{FR,disp} = P_b^{FR} \sum_{s=1}^S (T^{sec} P_{b,t,s}^{FR,\%}) \quad (10)$$

Where, the superscript ‘FR’ represents DC, FFRL and FFRH. In (10), the fraction of power dispatched ($P_{b,t,s}^{FR,\%}$) in each time step is multiplied by $T^{sec} = 1/60^2$ to convert to kWh per kW of power committed. This is summed to give the fraction of power in each time step. Then multiplied by the committed power capacity determined by the operational optimisation, which gives the power dispatched in each time step. The DC response energy payment received is 0, whereas the FFR high and low response energy payments are related to the balancing price [20].

$$K_{b,t}^{FFR,disp} = \begin{cases} -0.75K_{b,t}^{bal}, E_{b,t}^{FFR,disp} < 0 \\ 1.25K_{b,t}^{bal}, E_{b,t}^{FFR,disp} > 0 \end{cases} \quad (11)$$

In (11) when energy is exported in response to low frequency, the price received is 125% of the balancing price in that time step. When energy is imported in response to high frequency, the price paid for the energy is 75% of the balancing price. Assuming the LES must purchase energy earlier or sell it later at the balancing price, the benefit of responding is a 25% difference in price (for exporting this is 125% minus 100%, for importing this is 100% minus 75%). Therefore, the following equation was defined to give the financial benefit of dispatching for FFR high and low.

$$\phi^{FR,disp} = \sum_{b=1}^B \sum_{t=1}^T (0.25K_{b,t}^{bal} E_{b,t}^{FFR,disp}) \quad (12)$$

The final income for dispatching FFRL and FFRH was the sum of dispatched energy in each time step multiplied by the balancing price and 0.25. The dispatching income was calculated outside of the operational optimisation, therefore does not influence the power committed to each service. The service dispatch model was formulated and run in

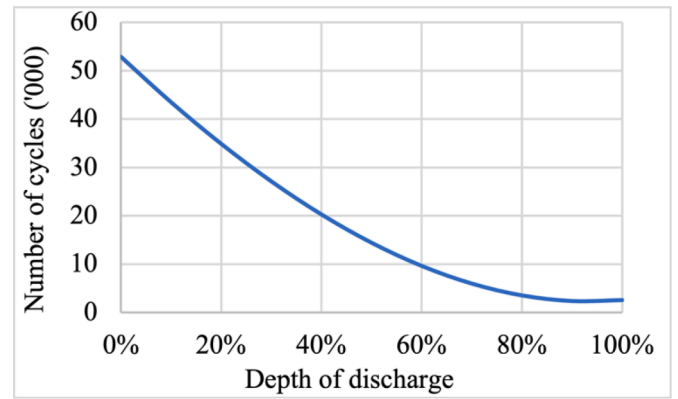


Fig. 4. Maximum number of charge/discharge cycles at specific depths of discharge. Showing a non-linear relationship [25].

MATLAB.

2.3. Battery degradation

Modelling battery degradation is complex and depends on many factors including cell chemistry, energy throughput and operating conditions such as depth of discharge, temperature and voltage. Commonly, battery degradation is divided into calendar and cyclic aging [21]. Calendar aging is the loss of usable energy capacity over time, with no charge/discharge cycles. Cyclic aging is capacity fade due to charging and discharging cycles, which is significantly affected by the depth of discharge. Typically, a stationary lithium-ion BSS reaches end-of-life at 70–80% of its starting energy capacity [22,23].

Calendar aging: The calendar aging model was inspired by [24]. The model is a linear depreciation over a 20-year shelf life, where the battery reaches end-of-life at 80% energy capacity, resulting in a daily energy capacity depreciation of:

$$D_{day}^{cal} = \frac{capacity\ loss}{days * years} = \frac{20\%}{365 * 20} = 0.00274\%. \quad (13)$$

Cyclic aging: In the cycle aging model, the number of cycles and the depth of discharge were considered. Fig. 4 shows the relationship between depth of discharge and the number of cycles for a lithium-ion battery [25]. This shows a non-linear characteristic, where high depths of discharge significantly reduce maximum number of cycles. The degradation characteristic in Fig. 4 was applied to the methodology from [24], to determine the cyclic battery aging for each day, accounting for depth of charge/discharge cycles. The degradation in each time step was calculated as follows.

$$D_t^{cyc} = 0.5 \left| \frac{1}{N_t^{cyc}} - \frac{1}{N_{t-1}^{cyc}} \right| \quad (14)$$

Where, N_t^{cyc} is the number of cycles corresponding to the depth of discharge, defined using the characteristic in Fig. 4, with the following equation:

$$N_t^{cyc} = 12,198DOD_t^3 + 34,954DOD_t^2 - 97,517DOD_t + 52,895 \quad (15)$$

Where, $DOD_t = (E^{max} - E_t)/E^{max}$. This formulation estimates battery degradation between the current time step and the previous time step. The 0.5 multiplier indicates each charge/discharge process is half of a full cycle. The degradation for each day was determined by summing degradation between each time step for the whole day, as shown below.

$$D_{day}^{cyc} = \sum_{t=1}^{24} D_t^{cyc} \quad (16)$$

Cyclic aging: For each day of the year, battery degradation was set as the larger of calendar and cyclic degradation, as shown in (17).

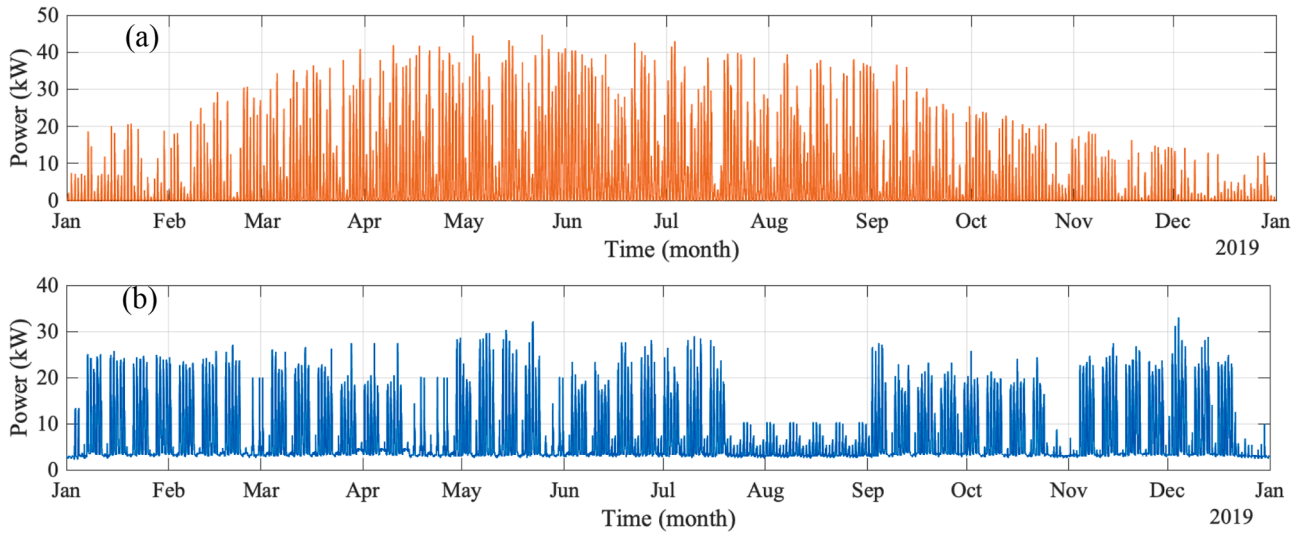


Fig. 5. LES (a) PV generation and (b) local school demand inputs for 2019.

$$D_{day}^{total} = \max\{D_{day}^{cal}, D_{day}^{cyc}\} \quad (17)$$

The total battery degradation for the year was found by summing the degradation for each day, for the whole year, as shown below.

$$D^{PA} = \sum_{day=1}^{365} D_{day}^{total} \quad (18)$$

Where, D^{PA} is the battery degradation due to price arbitrage operation and does not include frequency response delivery. The methodology so far does not consider degradation due to energy delivered for frequency response. To account for this, the proportion of energy throughput due to frequency response delivery was assumed to be the same as the proportion of degradation due to frequency response delivery. Therefore,

$$D^{Total} = D^{PA} \left(1 + \frac{Dispatch\ energy\ throughput}{PA\ energy\ throughput} \right) \quad (19)$$

Where, *Dispatch energy throughput* is an output of the energy dispatch model and *PA energy throughput* is an output of the operational optimisation. D^{Total} is total degradation and includes both degradation from price arbitrage operation and from dispatching energy in response to changes in frequency. The battery degradation modelling was carried out using Excel.

2.4. Net present value

The cumulative NPV was calculated using the outputs of the operational optimisation and the battery degradation calculation. The cumulative NPV was calculated using (20).

$$NPV = -I + \sum_{y=1}^Y \left(\frac{OCS_y}{(1+i)^y} \right). \quad (20)$$

Where, I is the investment cost, y is the year ($y = 1, \dots, Y$), OCS_y is the operational cost savings and i is the discount rate. OCS_y is the operating cost without a BSS, minus the operating cost with a BSS. The operating cost with a BSS includes savings from price arbitrage, frequency response availability revenue and frequency response delivery revenue. OCS_y was calculated for each year of the battery's lifetime. To account for battery degradation, the battery capacity (E^{max}) in the operational optimisation was updated each year using the battery degradation calculated for the previous year. As shown in Fig. 2, this process was repeated for every iteration of y until the battery reached its end-of-life



Fig. 6. Rolling weekly average wholesale electricity price in 2019 [26].

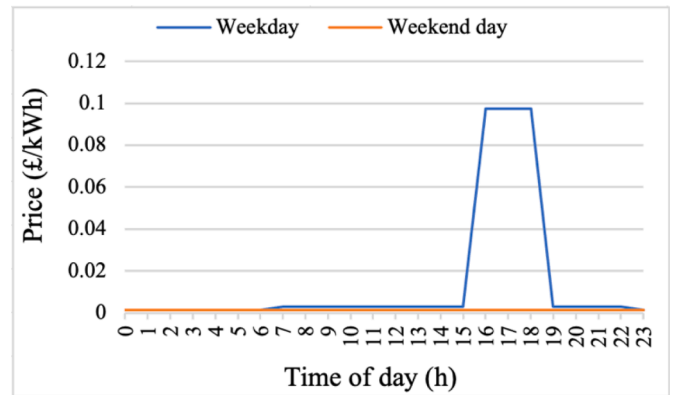


Fig. 7. Daily DUoS charges for weekdays and weekends.

at 80% of its original energy capacity. Each iteration of the NPV calculation included all OCS_y terms from previous years, with Y increasing by 1 for each iteration. Excel was used to calculate NPV.

3. Case study definition

The LES case study was based on a school in Cardiff with 50 kW of PV panels and a BSS with 10 kW power rating and 20 kWh energy capacity.

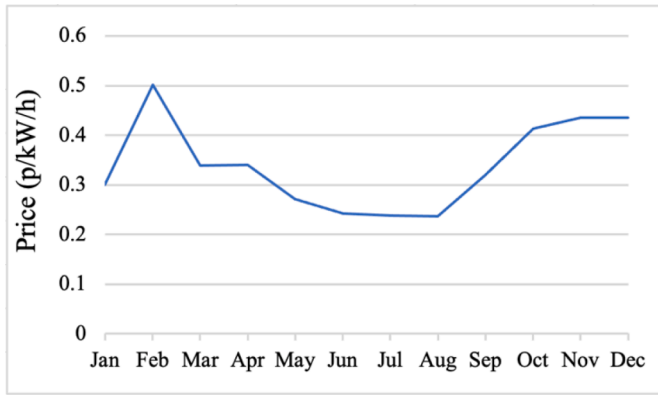


Fig. 8. Monthly average availability price for FFRH and FFRL.

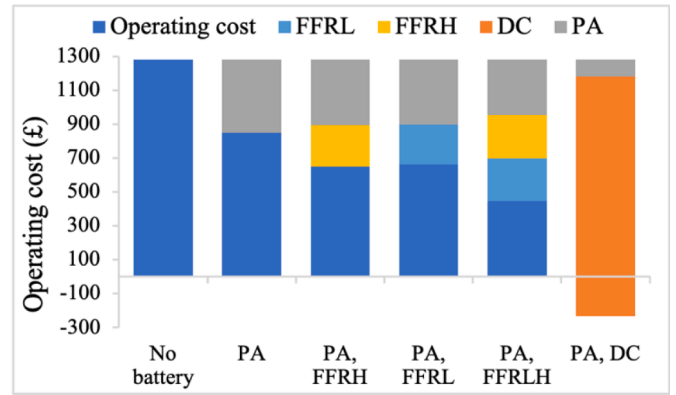


Fig. 9. Operating cost for each scenario in the first year of BSS operation. Cost savings from each service are shown for each scenario.

The battery was assumed to have a round trip efficiency of 90%, which was applied as a charging/discharging efficiency of 94.87%. Hourly time intervals ($\tau = 1$) were used, for the year 2019. The initial battery state of charge (E^{ini}) was defined for the first time step, on the first day of the year and was set to 50% of the battery energy capacity. No limit was set for depth of discharge, meaning state of charge could vary between 0% and 100%. The final battery state of charge, in the last time step, on the last day of the year was set as equal to or larger than the initial state of charge. PV generation and local demand were inputs and are shown in Fig. 5. The LES import and export prices were defined as the wholesale day-ahead electricity price, where the rolling weekly average is shown in Fig. 6. The import power was also subject to DUoS charges, shown in Fig. 7. In reality, the LES is too small to directly participate in the wholesale electricity market and frequency response services. However, small LESs can be aggregated to meet technical requirements for these markets, such as minimum capacity limits [18].

The availability price paid for DC was 1.7 p/kWh, which was the most consistently accepted bid price for DC [27]. The availability price for FFR varies from block to block and throughout the year. Prices for a week in each month of 2019 were acquired from market outcome data [28]. These prices were repeated for the duration of each month to give the availability price. The monthly average is shown in Fig. 8. The price for FFRH and FFRL were assumed to be the same. Five scenarios were defined with a different combination of services.

- 1 PA only
- 2 PA & FFRL
- 3 PA & FFRH
- 4 PA, FFRL & FFRH
- 5 PA & DC

PA only is the typical operation with no participation in frequency response services. FFR services can be stacked together, therefore a combination of FFRL and FFRH was evaluated in Scenario 4. DC cannot be stacked with other frequency response services so was stacked with PA only. To evaluate operation with PA only, a constraint was set to limit the maximum frequency response power to 0. This process was repeated to give results for every year of the BSSs lifetime, as shown in Fig. 2.

4. Results and discussion

4.1. Economic evaluation of battery storage

The economic viability of LES revenue stacking was evaluated in three ways: change in operating cost, NPV and the income from dispatching energy in response to changing frequency.

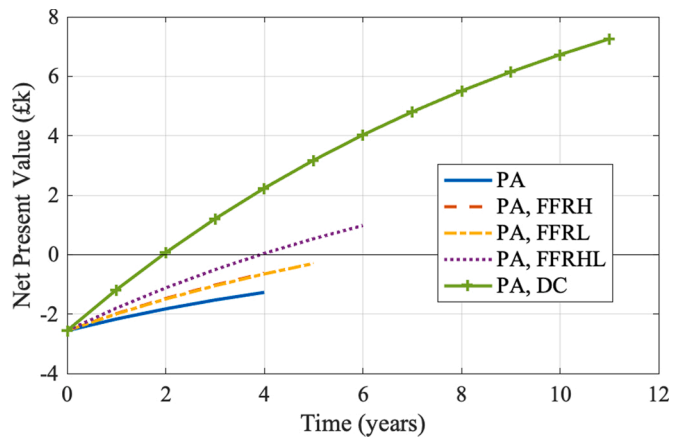


Fig. 10. Cumulative NPV for each operating scenario, until battery end-of-life was reached at 80% capacity.

4.1.1. Local energy system operating cost

The operation of the LES was evaluated using the operational optimisation described in Section II.A. The operating cost results are for the first year of operating with the BSS. For Scenarios 1 – 5, the total operating cost and break down of operating cost savings from each market are shown in Fig. 9. Also shown is the total operating cost for the LES with no BSS, which was £1279.94. All operating strategies reduced the LES operating cost. The conventional operating strategy PA only resulted in the lowest operating cost savings, reducing operating cost by 33.7%. Participating in FFR low, high or both further reduced the LES operating cost. Stacking FFR high and low resulted in an operational cost saving of 65.2%. The scenario with the largest impact on operating cost was Scenario 5, stacking PA with DC. The contribution to operating cost savings made by PA was the lowest out of all scenarios. However, DC produced enough revenue to reduce the operating cost by 118.2%, converting the operating cost into an operating income.

4.1.2. Investment viability

The evaluation of investment presents the yearly NPV for each operating scenario, accounting for battery degradation. These results are for a capital cost of \$177/kWh or approximately £128/kWh, which was the average price of stationary BSSs in 2020 [6]. Fig. 10 presents the yearly NPV for each operating scenario, until the battery end-of-life at 80% of its original energy capacity. PA only resulted in the lowest NPV with Scenarios 1, 2 and 3 resulted in a negative NPV at battery end-of-life, indicating an unattractive investment. Scenarios 4 and 5 produced positive NPVs over the battery lifetime, indicating worthwhile investments. The scenario with the largest NPV and longest battery

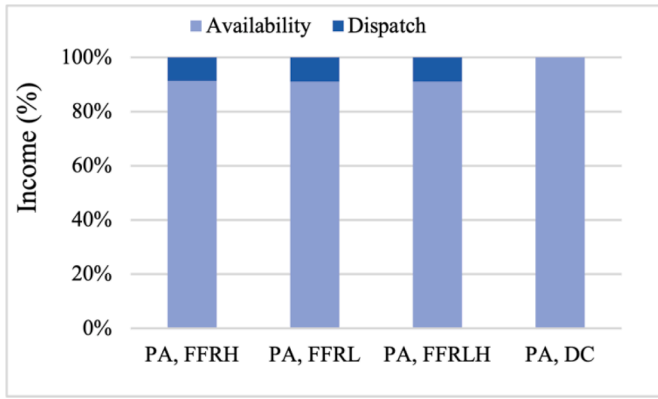


Fig. 11. Total income attributed to availability of power capacity and delivery of energy, for the first year of BSS operation.

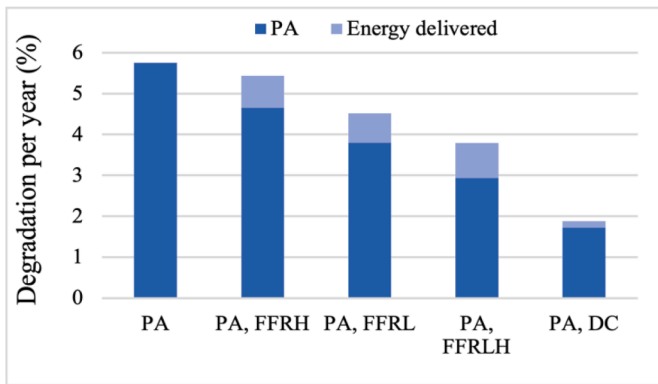


Fig. 12. Battery degradation from PA operation and frequency response energy delivered, in the first year of BSS operation.

lifetime was Scenario 5 (PA and DC), with a NPV of £7255.42 and a lifetime of 11 years. The result in Fig. 10 is in line with [8,12] and demonstrates that participating in frequency response services can not only improve investment viability but also extend the lifetime of the BSS.

Stationary BSSs on power grids are large whereas the LES in this study is much smaller. Domestic stationary BSS prices are higher, ranging from £445/kWh to £1315/kWh [29]. At these prices, only Scenario 5, with PA and DC, achieved a positive NPV over the battery lifetime. Although, the NPV was only positive up to a capital cost of approximately £490/kWh. Analysis of BSS prices shows that despite revenue stacking improving investment viability of BSSs, the cost of small-scale BSSs will limit their mass adoption.

4.1.3. Frequency response energy dispatch income

The model presented in Section II.B was used to determine the total energy dispatched for each service, as well as the total revenue for dispatching energy into the power grid. Fig. 11 shows the total income split into revenue from making power capacity availability and dispatching energy, for the first year of BSS operation. As there is no response energy payment for DC, all the revenue for DC was from the availability payment. Most of the income for FFR high and low was also from the availability payments, with revenue from response energy payments making up approximately 9% of total income for these services. This result shows the importance of availability revenue over dispatch revenue when considering participation in these frequency response services.

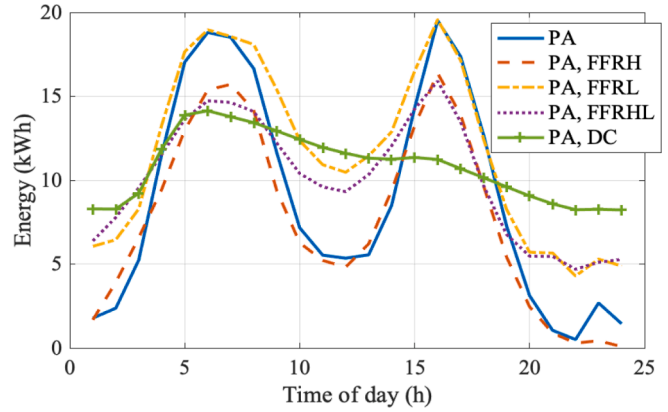


Fig. 13. Hourly average battery state of charge throughout the first year of BSS operation.

4.2. Battery degradation

Battery degradation is a vital consideration when investigating operation of BSSs. The model described in Section II.C was used to determine the battery degradation. Fig. 12 shows the percentage battery degradation for each scenario, in the first year of BSS operation. The results are split into the degradation related to PA operation and frequency response energy dispatched during service delivery. In all scenarios, most of the degradation resulted from charging/discharging for PA, with the highest overall degradation being the Scenario 1, with PA only. This result shows that participating in these frequency response markets not only improves battery operating cost and NPV but also reduces battery degradation, extending the lifetime of the battery. This result reflects the extended lifetime of the battery storage system in [8], for scenarios with no price arbitrage.

The benefits realised by frequency response services are due to the type of revenue. For PA, revenue is gained based on the volume of energy traded, therefore the battery must be charged/discharged to gain revenue. In contrast, frequency response services gain revenue based on the time that power capacity is available. Therefore, these services gain most of their revenue regardless of their charging/discharging cycles.

Assessing the operating cost, NPV and degradation has shown that the combination of PA and DC was the most beneficial for the LES. Due to the high price and low discharge rate, PA with DC resulted in the highest financial reward and the longest lifetime of the battery. The amount of degradation is subject to various environmental and operating conditions. In particular, charge and discharge cycling, battery chemistry and battery manufacturer. In this case study, the battery was able to fully discharge. Allowing 100% depth of discharge can result in higher degradation rates. The depth of discharge can be limited to reduce battery degradation. Battery degradation is highly sensitive to the number of cycles and depth of discharge. Therefore, accurate estimation of battery degradation must account for these characteristics.

4.3. Battery operation

The reduction in battery degradation when participating in frequency response services is reflected in the operating characteristics of the BSS. Fig. 13 presents the hourly average battery state of charge throughout the year, for the first year of BSS operation. Out of all scenarios shown in Fig. 13, PA only had the widest variation in average energy stored in the battery. Being amongst the lowest during midday and night, while being amongst the highest during morning and early evening and going through two large charge/discharge cycles. In contrast, Scenario 5 (DC stacked with PA) has the highest energy stored in the battery during midday and evening, while having the lowest during morning and early evening and having the least variation

Table 3
Average committed power capacity.

	FFRH	FFRL	FFRHL FFRH	FFRL	DC
Average committed power capacity (%)	76	80	78	84	95

throughout the 24 h. The results in this figure add to the discussion in Section IV.B and showcase the reduction in charge/discharge cycles and the average depth of discharge when participating in frequency response services.

The state of charge of the battery was also dictated by the amount of power committed to each service. When more power is committed to a service, more energy must be stored in the battery, so the service can be delivered. To demonstrate this, Table 3 presents the average power capacity committed to each service over the full time horizon.

5. Conclusion

This paper presents a linear optimisation approach to model local energy systems participating in the wholesale day-ahead electricity market and stacking multiple frequency response ancillary services. The approach was applied to a school case study to demonstrate its practicality. In addition, net present value was used to assess the investment case for a battery storage system participating in energy and frequency response markets, considering battery degradation. The revenue from energy dispatched in response to change in frequency was found using power system frequency. Battery degradation was also assessed, accounting for the number of cycles and their depth of discharge.

The operational optimisation showed that stacking frequency response services with price arbitrage resulted in lower operating costs for the local energy system. Similarly, the net present value of the battery investment was increased when stacking frequency response services. In both cases, price arbitrage with Dynamic Containment was the most profitable combination. The majority of frequency response revenue came from availability payments, making up over 90% of Firm Frequency Response revenue and all the Dynamic Containment revenue. Finally, the degradation model showed that participating in frequency response services reduces battery degradation, increasing the lifetime of the battery and improving the investment prospect and lifetime of the battery.

The methodology presented in this study can be applied to a wide variety of ancillary services and local energy system configurations. Future work could incorporate battery degradation in the operational optimisation and add constraints to limit degradation. Additionally, model developments could account for the impact of local energy system revenue stacking on other actors in the power system, such as flexibility aggregators, retailers and power system operators.

CRedit authorship contribution statement

William Seward: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Meysam Qadrdan:** Conceptualization, Methodology, Validation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Nick Jenkins:** Conceptualization, Writing – review & editing, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] Piclo, Element Energy, G. Oakes, Modelling the GB Flexibility Market Part 1: The Value of Flexibility, Oxford, 2020.
- [2] Future Energy Scenarios, National Grid ESO, Warwick, UK, 2021.
- [3] Energy Systems Catapult and Good Energy, "Renewable nation: pathways to a zero carbon Britain," Chippenham, 2021.
- [4] A. Kadri, K. Raahemifar, Optimal sizing and scheduling of battery storage system incorporated with PV for energy arbitrage in three different electricity markets, in: 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE), 2019, pp. 1–6.
- [5] Western Power Distribution, About flexibility services, Flex. Power (2021) [Online]. Available: <https://www.flexiblepower.co.uk/about-flexibility-services> [Accessed: 07-Feb-2022].
- [6] National Grid ESO, Balancing services, Ind. Inf. (2021) [Online]. Available: <https://www.nationalgrideso.com/industry-information/balancing-services> [Accessed: 07-Feb-2022].
- [7] N. Bullard, "This is the dawning of the age of the battery," Bloomberg Green, 2020. [Online]. Available: <https://www.bloomberg.com/news/articles/2020-12-17/this-is-the-dawning-of-the-age-of-the-battery>. [Accessed: 01-Feb-2021].
- [8] S. Englberger, A. Jossen, H. Hesse, Unlocking the potential of battery storage with the dynamic stacking of multiple applications, Cell Reports Phys. Sci. 1 (11) (2020), 100238.
- [9] A. Daggett, M. Qadrdan, N. Jenkins, Feasibility of a battery storage system for a renewable energy park operating with price arbitrage, in: 2017 IEEE PES Innov. Smart Grid Technol. Conf. Eur. ISGT-Europe 2017 - Proc, 2017, pp. 1–6.
- [10] Y. Song, et al., Optimal investment strategies for solar energy based systems, Energies 12 (14) (2019).
- [11] P.E. Campana, et al., Li-ion batteries for peak shaving, price arbitrage, and photovoltaic self-consumption in commercial buildings: a Monte Carlo analysis, Energy Convers. Manag. 234 (2021).
- [12] H.C. Hesse, M. Schimpe, D. Kucevic, A. Jossen, Lithium-ion battery storage for the grid - A review of stationary battery storage system design tailored for applications in modern power grids, Energies 10 (12) (2017).
- [13] A. Stephan, B. Battke, M.D. Beuse, J.H. C.lausdeinken, T.S. Schmidt, Limiting the public cost of stationary battery deployment by combining applications, Nat. Energy 1 (7) (2016) 1–9.
- [14] M. Merten, C. Olk, I. Schoeneberger, D.U. Sauer, Bidding strategy for battery storage systems in the secondary control reserve market, Appl. Energy 268 (2020), 114951.
- [15] L. Maeyaert, L. Vandeveld, T. Döring, Battery storage for ancillary services in smart distribution grids, J. Energy Storage 30 (2020).
- [16] Flexibility & Flexible Power," Smarter Networks, Western Power Distribution, 2021 [Online]. Available: <https://www.westernpower.co.uk/smarter-networks/flexibility-and-flexible-power> [Accessed: 04-Apr-2022].
- [17] Frequency Response Services," Balancing Services, National Grid ESO, 2022 [Online]. Available: <https://www.nationalgrideso.com/industry-information/balancing-services/frequency-response-services> [Accessed: 11-Apr-2022].
- [18] Dynamic Containment: Participation Guidance Document, National Grid ESO, Warwick, UK, 2021.
- [19] Historic Frequency data," Frequency response Services, National Grid ESO, 2020 [Online]. Available: <https://www.nationalgrideso.com/industry-information/balancing-services/frequency-response-services/historic-frequency-data> [Accessed: 17-Aug-2021].
- [20] CUSC Section 4 - Balancing Services, National Grid and National Grid ESO, Warwick, UK, 2017.
- [21] F. Berglund, S. Zaferanlouei, M. Korpas, K. Uhlen, Optimal operation of battery storage for a subscribed capacity-based power tariff prosumer-a Norwegian case study, Energies 12 (23) (2019).
- [22] Tesla, "Tesla powerwall warranty (European warranty region)," 2017.
- [23] Limited Warranty for RESU Prime Home Battery of LG Energy Solution, LG Energy Solution, Seoul, South Korea, 2021.

- [24] Y. Wang, Z. Zhou, A. Botterud, K. Zhang, Q. Ding, Stochastic coordinated operation of wind and battery energy storage system considering battery degradation, *J. Mod. Power Syst. Clean Energy* 4 (4) (2016) 581–592.
- [25] N. Omar, et al., Lithium iron phosphate based battery - Assessment of the aging parameters and development of cycle life model, *Appl. Energy* 113 (2014) 1575–1585.
- [26] Entsoe, “Day-ahead prices,” Transparency platform, 2021. [Online]. Available: <https://transparency.entsoe.eu/transmission-domain/r2/dayAheadPrices/show?name=&defaultValue=false&viewType=TABLE&areaType=BZN&atch=false&dateTime.dateTime=27.10.2019+00:00%7CCET%7CDAY&biddingZone.values=CTY%7C10Y1001A1001A92E!BZN%7C10YGB———A&resol>. [Accessed: 22-Feb-2022].
- [27] Dynamic Containment Data,” *Ancillary Services*, National Grid ESO, 2021 [Online]. Available: <https://data.nationalgrideso.com/ancillary-services/dynamic-containm ent-data> [Accessed: 17-Aug-2021].
- [28] Phase 2: FFR Auction Results Summary,” *Ancillary Services*, National Grid ESO, 2021 [Online]. Available: <https://data.nationalgrideso.com/ancillary-services/ph ase-2-ffr-auction-results-summary#> [Accessed: 17-Aug-2021].
- [29] Naked Solar, Solar batteries & storage, Storage (2021) [Online]. Available: <https://naked solar.co.uk/storage/> [Accessed: 17-Aug-2021].