Quantifying the value of distributed battery storage to the operation of a low carbon power system

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Abstract*—Battery storage provides flexibility to the power system and supports the increased integration of renewable energy sources. Distributed battery storage systems that are behind the meter are operated by their local owners, whose objectives may not align with those of the national power system. This paper presents a Bilevel optimisation approach to investigate the exchange of electricity between distributed battery storage and the national power system. The independent operating objectives of the battery storage systems are explicitly considered to assess their impact on the operation of the national power system. A comparison with a Centralised optimisation approach, that assumes a single objective function for the whole system, shows that the Bilevel optimisation approach captures the independencies of distributed battery storage objectives, while accounting for its interactions with the wider power system. The results show that the Centralised optimisation approach tends to overestimate the value of distributed battery storage for the power system. The results also highlight the influence of the retail contract structure in maximising the value of distributed battery storage for the national power system.

***Index Terms*— Distributed battery storage, price arbitrage, flexibility, national power system, local energy system.**

Nomenclature

Acronyms

CCGT	Combined cycle gas turbine
KKT	Karush-Kuhn-Tucker
LES	Local energy system
NPS	National Power System
OCGT	Open-cycle gas turbine
PV	Photovoltaic

Indices

j	Conventional generation index
t	Time index

Constants

C^{bat}	Total battery energy capacity (MWh)
C^{PS}	Pumped storage energy capacity (MWh)
E^{bat_max}	Maximum battery state of charge limit (%)
E^{bat_min}	Minimum battery state of charge limit (%)
J	Number of conventional generation types
K^b	Marginal cost of biomass generation (£/MWh)
K^h	Marginal cost of hydro generation (£/MWh)
K_j^{gen}	Marginal cost of conventional generation (£/MWh)
K^w	Marginal cost of wind generation (£/MWh)
K_t^{ex}	LES retail contract sell price (£/MWh)
K_t^{im}	LES retail contract purchase price (£/MWh)
P^{bat_max}	Total battery power capacity (MW)
P^{ex_max}	Maximum power exchange between local energy systems and the grid (MW)
P_j^{max}	Maximum power generation limit by conventional technologies (MW)
P_j^{min}	Minimum power generation limit by conventional technologies (MW)
P^{PS_max}	Maximum pumped storage charge/discharge power (MW)
P_t^b	Power generated by biomass (MW)
P_t^h	Power generated by hydro (MW)
$P_t^{L\_D}$	Total local power demand (MW)
$P_t^{N\_D}$	Inflexible national power demand (MW)
P_t^{PV}	Total PV power generation (MW)
$P_t^{w\_max}$	Maximum available wind generation (MW)
RDN_j	Conventional generation ramp down limit (MW/h)
RUP_j	Conventional generation ramp up limit (MW/h)
T	Number of time steps
η^{bat_ch}	Battery charging efficiency (%)
η^{bat_dis}	Battery discharging efficiency (%)
η^{PS}	Pumped storage round trip efficiency (%)
τ	Time interval (0.5 hours)

Variables

E_t^{bat}	Total energy stored in batteries (MWh)
E_t^{PS}	Energy stored in pumped storage (MWh)
$P_t^{bat\_ch}$	Total battery charging power (MW)
$P_t^{bat\_dis}$	Total battery discharging power (MW)
P_t^{ex}	Power exported from local energy systems (MW)
P_t^{im}	Power imported to local energy systems (MW)
$P_t^{PS\_ch}$	Pumped storage charging power (MW)
$P_t^{PS\_dis}$	Pumped storage discharging power (MW)
P_t^w	Wind power injected into grid (MW)
$P_{t,j}^{gen}$	Conventional power generation (MW)

I. Introduction

A rapid rise in the deployment of renewables has been seen in a bid to lower greenhouse gas emissions from the power sector. The increase in intermittent renewable generation leads to greater variability of generation. This, alongside the reduction of fossil fuel generation, a traditional source of supply-side flexibility, raises challenges related to balancing of supply and demand, ensuring security of power supply and effective use of renewables. Power system flexibility is the ability to alter generation or consumption in reaction to an external signal, to support the balancing of electricity supply and demand [1]. The flexibility available from storage systems is forecast to significantly increase alongside renewable generation, with this increase predominantly from battery storage [2]. Battery storage systems can provide flexibility to support the integration of intermittent renewable generation by managing the balance of electricity supply and demand [3].

Battery storage systems can provide a number of behind and in front of the meter services, such as: frequency regulation, voltage regulation, demand response and congestion management [4]. Small scale, behind the meter or distributed battery storage is a source of demand side flexibility that can be used to maximise renewable self-consumption at a local level [5], [6]. Large numbers of distributed battery storage systems can increase system wide flexibility, helping to balance supply and demand and reducing renewable curtailment [7]. However, distributed battery storage systems act to optimise their own operating objectives. As a result, the storage operator may choose to import/export power at a time that increases operating costs for the whole power system.

The independent nature of the storage operators' objectives raises challenges such as how to realistically quantify the value of distributed battery storage for the owner and the national power system (NPS). Additionally, how to align decisions made by the storage system operator with the objectives of the NPS. Hence, it is necessary to address the design of retail contracts which can influence the behaviour of the storage operator, to align their objectives with the whole system.

The existing literature presents various methodologies for investigating the interactions between distributed flexibility and NPS operation. According to Awnar et al. [8], these can be broadly classified into two categories. The first, "Centralised Optimisations" and the second "Strategic Market Based methods". Centralised optimisations consider the operation of distributed flexibility from the whole system perspective. They tend to be dispatch models, that optimise the operation of conventional and renewable generators, as well as storage. In centralised optimisations, the demand side flexibility tends to be integrated into the whole system, assuming centralised control, see Fig. 1.

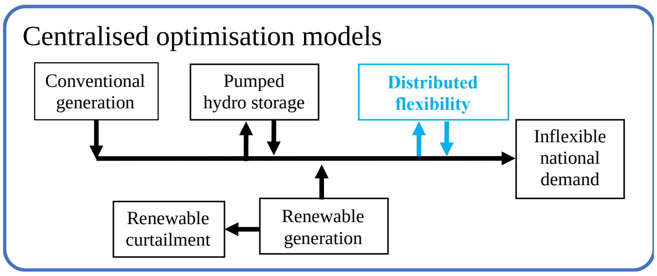

Fig. 1. Centralised optimisation model structure. The centrally operated distributed flexibility is integrated within the whole system. Black arrows are power exchange in the national power grid, light blue arrows represent the power exchange with the local energy systems.

As an early example, Roscoe and Ault [9] acknowledged the increasing relevance of demand side flexibility, to support an increased proportion of renewable generation. In [9], simple elastic demand is operated based on dynamic prices. More recently, studies have implemented detailed thermal models for demand response from electrified heating within a centralised whole power system optimisation. Anwar et al. [10] considered demand response from electrified heating systems to assess the value of load shifting and price arbitrage. Similarly, Patteeuw et al. [11] focused on understanding the interactions between the demand and supply side of the power system with demand response from electrified heating. Wang et al. [12] created an integrated unit commitment model that assesses the interactions between plug-in hybrid electric vehicles, wind power and demand response with the wider power system. These studies demonstrate the importance of integrated models that consider distributed flexibility. However, the flexible assets are assumed to be centrally operated. Therefore, these studies do not account for the independent objectives and strategic behaviour of the flexibility owners. They represent an overall, whole system optimal solution, rather than the realistic interactions between independent entities.

Several studies have advanced integrated modelling of flexible assets by accounting for the independency of wholesale, retail and/or consumer behaviour. Bilevel optimisation has been used for modelling such characteristics. Sinha et al. [15] define a bilevel optimisation as a "mathematical program, where an optimisation problem contains another optimisation problem as a constraint". Bilevel optimisations have a hierarchical structure, in which each level has its own objective and set of constraints. For further details and the mathematical standard form, refer to [15].

A hierarchical decision-making framework is presented by Bahramara et al. [13]. The study investigated the interactions between a distribution company and several micro-grids. More recently, Anwar and O'Malley [14] considered the participation of a demand response aggregator in the electricity market. Their work has been advanced with the inclusion of a consumer optimisation [8]. These studies report bilevel models of energy systems with distributed flexibility and compare them with equivalent centralised optimisation models. They conclude that centralised models tend to overestimate the value of the flexibility for the whole system.

Several studies utilise bilevel optimisation to focus on the interactions between actors in the energy system. Zugno et al. [16] and Forouzandehmehr et al. [17] studied the interactions between retailers and their customers, with demand response from electrified heating and energy storage. Bahramara et al. [13], [18] and Fateh et al. [19] focused on the behaviour of flexible microgrids in relation to prices set by a retailer. Although this provides valuable insights into retailer profitability when trading with flexible customers, they do not account for the impact on the NPS. Bahramara et al. [20] also considered flexible assets integrated into distribution companies, participating in a wider power system model. Anwar and O'Malley [14] integrated consumer thermal demand response flexibility with a load aggregator competing in wholesale and reserve markets. These studies show the importance of accounting for impacts on the whole system. However, the strategic behaviour of distributed flexibility asset owners is neglected. In a later study, Anwar et al. [8] created a single leader, multiple follower bilevel optimisation to evaluate the strategic decision making of a retailer, a system operator (clearing the wholesale energy market), and consumers. In this case, the objectives of all three actors are explicitly considered. The results of this study demonstrate the importance of considering independent objectives and the major role that retail contract design plays in the value of distributed flexibility.

Zugno et al. [16] studied dynamic, time-of-use and fixed tariffs offered by a retailer, to customers. The dynamic contract resulted in reduced market cost for the retailer in comparison to time-of-use and fixed contracts. This reduction was assumed to reflect an increase in social welfare, which was considered as a proxy for the reduction of generation cost. This study provides insights into the benefits of dynamic price contracts for consumers and retailers. However, it does not consider the operation of the whole power system, which is a key part of understanding how distributed flexibility can support the integration of renewable generation.

To address the challenges associated with independently operated distributed flexibility, an integrated model that considers the objectives of all actors is required. To evaluate the value of distributed flexibility, the whole system operation must be considered. This paper aims to explore the efficacy of a *Bilevel* optimisation approach for studying the interactions between multiple actors in a hierarchical energy system. Focussing on assessing the value of flexibility from distributed battery storage, for application in price arbitrage. Furthermore, to investigate distributed battery storage operation, in relation to realistic retail contracts and the impact of the operation of national generation. The key contributions are as follows.

- The study accounts for the independencies of different actors in the energy system applying bilevel optimisation to a case study of a real energy system. Verifying the efficacy of bilevel optimisation for multi actor energy system modelling, by comparison with a *Centralised* optimisation approach.
- Different retail contracts are examined and their impact on the value of distributed battery storage assessed. Specifically, retail contracts are compared to reveal their impact on both LES and NPS operating costs.

The rest of this paper is structured as follows. Section 2 sets out the overall structure of the *Bilevel* optimisation and defines the upper and lower level optimisations in detail. Section 3 specifies the case study and provides input parameters. Section 4 describes the results of the *Bilevel* optimisation modelling and discusses the importance of the findings. Section 5 summarises and concludes.

II. Methodology

In the *Centralised* optimisation approach, the NPS schedules the generation plants and the operation of local battery storage systems. This model assumes central control over distributed flexibility and is demonstrated by replacing the "distributed flexibility" box in Fig. 1, with the "Leader" structure shown in Fig. 2. The objective function of the *Centralised* optimisation aims to minimise the total cost of meeting demand for the whole power system.

The *Bilevel* model proposed in this paper considers different objectives for two actors in the power system. Their interactions are represented by the power exchanged between local and national energy systems. Each LES aims to utilise their battery storage system to minimise their cost of meeting demand. The NPS reacts to the LES power requirements and minimises the operational cost of meeting overall national demand.

The LES was assumed to be a price taker in the retail market, purchasing electricity through currently available retail contracts. The operator of the LES makes the first

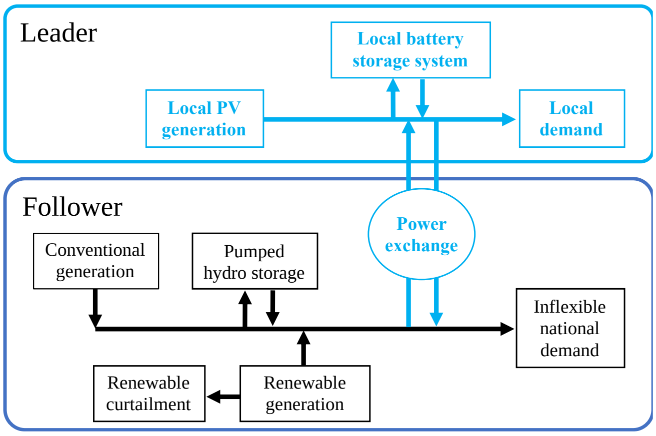

Fig. 2. Power exchange diagram showing the interactions between the local energy system and the national power system. Black arrows are power in the national power system, light blue arrows are power exchange with the local energy system.

decision (in the context of bilevel optimisation it is known as the 'leader' or 'upper level' problem) and then the operator of the NPS schedules the generation plants to meet the remaining electricity demand (the operator of the NPS is the 'follower' or 'lower level' problem). This structure is shown in Fig. 2.

A. *Upper level optimisation: minimising the operational cost of the local energy systems*

The LES has onsite renewable generation, which, in this case is photovoltaic (PV) panels. The LES also has a battery storage system, that is operated in response to a pre-determined retail contract. A single LES would have little impact on the whole power system. Hence, the model considers several identical LESs to be aggregated within the NPS. The upper level problem is represented by aggregated LES operation, seeking to minimise their operational cost. The objective function is defined as follows.

$$\text{Min} \sum_{t=1}^{T} \tau (K_t^{im} P_t^{im} - K_t^{ex} P_t^{ex}) \tag{1}$$

The objective function (1) minimises the LES operating cost, which is defined as the difference between the cost of importing electricity to satisfy demand ($K_t^{im} P_t^{im}$) and the revenue from selling electricity back to the grid ($K_t^{ex} P_t^{ex}$). Minimal cost is achieved through control of battery charging/discharging. Multiplication by the time interval (τ) ensures conversion from power to energy. The LES optimisation is subject to several constraints that are described below.

$$P_t^{PV} + P_t^{bat\_dis} + P_t^{im} = P_t^{L\_D} + P_t^{bat\_ch} + P_t^{ex}, \quad \forall t \in T \tag{2}$$

$$0 \le P_t^{im} \le P^{ex\_max}, \quad \forall t \in T \tag{3}$$

$$0 \le P_t^{ex} \le P^{ex\_max}, \quad \forall t \in T \tag{4}$$

Equation (2) ensures the power balance of the system, where, at each time step, PV generation (P_t^{PV}), battery discharge ($P_t^{bat\_dis}$) and import power (P_t^{im}) are equal to local demand ($P_t^{L\_D}$), battery charging power ($P_t^{bat\_ch}$) and export power (P_t^{ex}). Equations (3) and (4) constrain the power flow between NPS and LES.

$$0 \le P_t^{bat\_ch} \le P^{bat\_max}, \quad \forall t \in T \tag{5}$$

$$0 \leq P_t^{bat\_dis} \leq P^{bat\_max}, \quad \forall t \in T \tag{6}$$

$$E^{bat\_min} C^{bat} \leq E_t^{bat} \leq E^{bat\_max} C^{bat}, \quad \forall t \in T \tag{7}$$

$$E_t^{bat} = E_{t-1}^{bat} + \tau \left(\eta^{bat\_ch} P_t^{bat\_ch} - \frac{P_t^{bat\_dis}}{\eta^{bat\_dis}} \right), \forall t \in T \tag{8}$$

$$\sum_{t=1}^{T} \tau P_t^{bat\_ch} \leq C^{bat} \tag{9}$$

Equations (5)-(9) model the operation of the battery storage system. The battery charging/discharging power at each time step is restricted by the battery power rating in (5) and (6). In (7), the battery state of charge is limited to an operating range of energy storage capacity (C^{bat}), where state of charge can be limited to a maximum (E^{bat_max}) and minimum (E^{bat_min}) to prolong battery life by reducing degradation [21]. The battery power ratings and energy storage capacities are inputs to the model. The energy balance of the battery is shown in (8), giving the state of charge (E_t^{bat}), where its value depends on the state of the charge in the previous time step (E_{t-1}^{bat}) and the charging ($P_t^{bat\_ch}$) and discharging ($P_t^{bat\_dis}$) power. The charging efficiency (η^{bat_ch}) and discharging efficiency (η^{bat_dis}) of the battery are accounted for. Equation (9) limits the number of charge/discharge cycles by limiting the total energy stored in the battery over 24 hours. This equation is included to avoid excessive number of charge/discharge cycles that leads to degradation of the batteries.

B. *Lower level optimisation: minimising the operational cost of the national power system*

The lower level NPS optimisation coordinates the dispatch of conventional generation, the injection of renewable generation to the grid and the operation of pumped storage. The dispatch of conventional generation is based on merit order of their marginal generation cost. The time series of biomass and hydro generation data were given to the optimisation as input data. The wind generation time series gave the maximum wind power available, where any wind power not injected into the grid was curtailed. Pumped storage facilities were aggregated in terms of their energy and power capacity [14].

This problem aims to minimise the operating cost of power generation required to meet overall demand seen by the NPS. The objective function is defined as follows.

$$\text{Min} \quad \sum_{t=1}^{T} \tau \left(\sum_{j=1}^{J} \left(K_j^{gen} P_{t,j}^{gen} \right) + K^w P_t^w + K^b P_t^b + K^h P_t^h + K_t^{ex} P_t^{ex} \right) \tag{10}$$

The objective function (10) comprises the cost of electricity generation by conventional technologies ($K_j^{gen} P_{t,j}^{gen}$), wind ($K^w P_t^w$), biomass ($K^b P_t^b$), hydro ($K^h P_t^h$) and purchased power from LESs ($K_t^{ex} P_t^{ex}$). The power terms are multiplied by the time interval (τ) to convert from power to energy. The NPS optimisation is subject to several constraints which are described next. Corresponding dual variables are indicated next to each constraint.

$$\sum_{j=1}^{J} P_{t,j}^{gen} + P_t^{ex} + P_t^w + P_t^b + P_t^h + P_t^{PS\_dis} = P_t^{im} + P_t^{PS\_ch} + P_t^{N\_D} : \mu_t^1, \ \forall t \in T \tag{11}$$

The power balance of the NPS is expressed in (11). This ensures that the sum of conventional generation ($P_{t,j}^{gen}$), aggregated LES export power (P_t^{ex}), wind (P_t^w), biomass (P_t^b) and hydro (P_t^h) generation and discharge from pumped storage ($P_t^{PS\_dis}$) is equal to the aggregated LES import power (P_t^{im}), charging of pumped storage ($P_t^{PS\_ch}$) and the inflexible national demand ($P_t^{N\_D}$). Inflexible national demand is equal to total national demand minus the aggregated demand of LESs. Equations (12)-(13) bound the outputs of conventional and wind generation.

$$P_j^{min} \leq P_{t,j}^{gen} \leq P_j^{max} \ : \ \lambda_{t,j}^1, \lambda_{t,j}^2, \forall t, j \in T, J \tag{12}$$

$$0 \leq P_t^w \leq P_t^{w\_max} \ : \ \lambda_t^3, \lambda_t^4, \ \forall t \in T \tag{13}$$

The minimum (P_j^{min}) and maximum (P_j^{max}) output of conventional generation is given in (12), while the contribution of wind generation is bounded by available wind power ($P_t^{w\_max}$) during each time step, shown in equation (13). Any available wind that is not utilised, is curtailed

$$0 \leq P_t^{PS\_ch} \leq P^{PS\_max} \ : \ \lambda_t^5, \lambda_t^6, \ \forall t \in T \tag{14}$$

$$0 \leq P_t^{PS\_dis} \leq P^{PS\_max} \ : \ \lambda_t^7, \lambda_t^8, \quad \forall t \in T \tag{15}$$

$$0 \leq E_t^{PS} \leq C^{PS} \ : \ \lambda_t^9, \lambda_t^{10}, \quad \forall t \in T \tag{16}$$

$$E_t^{PS} = E_{t-1}^{PS} + \tau \left(\eta^{PS} P_t^{PS\_ch} - P_t^{PS\_dis} \right) : \mu_t^2, \ \forall t \in T \tag{17}$$

Pumped storage is operated based on equations (14)-(17). The charging power ($P_t^{PS\_ch}$) constraint is shown in (14) and the discharging power ($P_t^{PS\_dis}$) constraint is shown in (15). The pumped storage state of charge (E_t^{PS}) limit is given in equation (16). The energy balance of pumped storage is given in (17), where the state of charge is related to the value of state of the charge in the previous time step and the charging and discharging power. The round-trip efficiency (η^{PS}) is applied to the charging process.

As the lower level problem is linear, the *Bilevel* optimisation was solved using a set of Karush-Kuhn-Tucker (KKT) conditions that reformulated the problem as a single level non-linear optimisation. The non-linearities were linearized using the Fortunay-Amat application of the Big-M method [22]. Details of the reformulation are presented in the Appendix. The resulting single level optimisation is a mixed-integer linear optimisation problem, which was solved using commercial software. In this work, the problem was implemented in GAMS and solved using the CPLEX solver.

III. NUMERICAL CASE STUDY

The settlement period of the GB electricity market is 30 minutes [23]. Therefore, half hourly time intervals were used, over a 24-hour time horizon of operation. The analysis was carried out for a typical summer weekday during school holidays.

A. Local energy system characteristics

A school in Cardiff with 50 kW of PV panels and a planned battery storage of 20 kWh storage capacity and 10 kW power rating was used for the case study. Maximum import/export power flows, from all LESs, were set at 5 GW. The charging and discharging efficiencies of batteries were defined as 98% and 96% respectively [21]. The state of charge when $t = 0$ was 50% of the battery energy capacity. In this study, the state of charge of the batteries were able to vary between 0 and 100% of the storage capacity (i.e. $E^{bat\_min} = 0$ and $E^{bat\_max} = 1$). The battery state of charge at the final time step was equal to or larger than 50% of the battery energy capacity. 50,000 identical LESs were used to increase their impact on the NPS. PV generation and local demand were defined inputs to the model and are shown in Fig. 3. Assuming identical LESs is a limitation of this work. However, having a more diverse selection of LES archetypes would not change the conclusions of the study.

B. National power system characteristics

The NPS was based on a representation of the GB 2030 national generation mix. Three conventional generation technologies were considered: combined cycle gas turbine (CCGT), nuclear and open cycle gas turbine (OCGT). For CCGT and OCGT, their aggregated capacity within GB were given as their maximum power output. As the output of nuclear generation does not vary significantly over 24 hours, power output was limited to a small range, typical of a day during summer school holidays. Capacity, as well as marginal generation costs for conventional generation technologies are shown in Table 1. Conventional generation ramp rates were not accounted for in this study.

TABLE I
CONVENTIONAL GENERATION INPUT DATA [24], [27]–[29]

Technology	Maximum capacity (MW)	Minimum generation (MW)	Marginal cost (£/MWh)
CCGT	15,536	0	57
Nuclear	4,570	4,560	10.4
OCGT	1,126	0	83

Biomass and hydro generation, available wind generation and inflexible national demand were real time series data from a typical day during summer school holidays and were inputs to the optimisation model. A case with high national wind generation was used to emphasise the use of flexibility with high penetrations of renewable generation. Available power generation from wind was taken from historic data from the 31st July 2019, which was during summer school holidays [24]. The available wind generation and inflexible national demand are shown in Fig. 4.

Depending on levels of demand and generation from must run technologies (i.e., nuclear, hydro and biomass), a proportion of available wind generation could be curtailed. The inputs for national demand and wind, biomass and hydro generation were scaled in line with National Grid projections, to give inputs for 2030 [25]. Inflexible national demand was assumed to be the total national demand, minus the aggregated school demand. The pumped storage had a round-trip efficiency of 75% [26], while the energy storage capacity

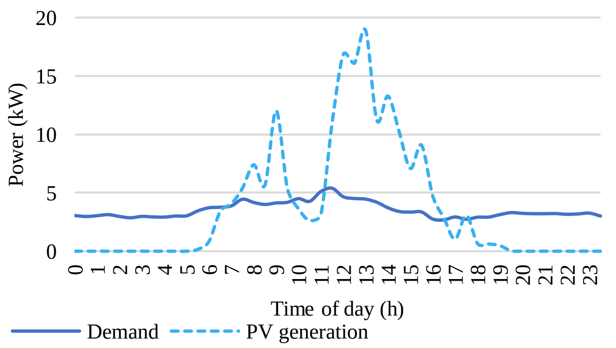

Fig. 3. School PV generation and demand for a typical weekday during summer school holidays. Steady demand throughout the day due to empty school, PV generation exceeding local demand at times during the day.

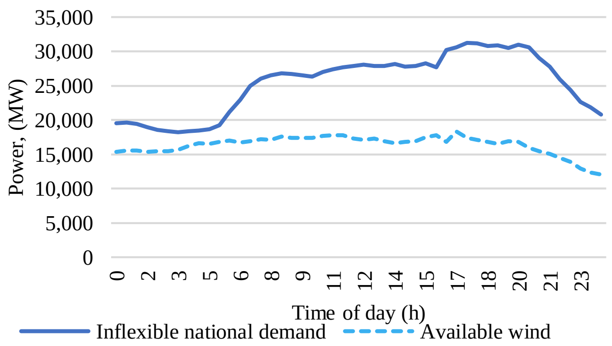

Fig. 4. Inflexible national demand and available wind generation for a typical weekday during summer school holidays. Demand is low during the night, increases in the morning and peaks in early evening.

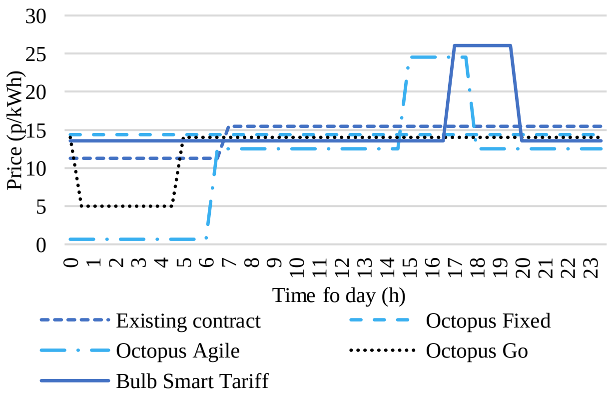

Fig. 5. Electricity import price in different retail contracts considered for comparing the value of battery storage in LESs. Two contracts increase prices during peak times. Three contracts reduce prices during the night.

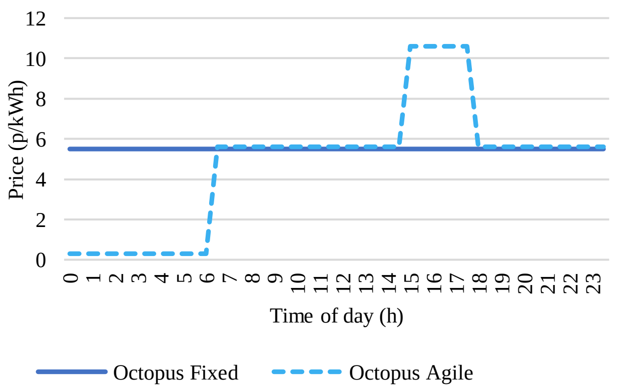

Fig. 6. Electricity export price in different retail contracts considered for the comparing the value of battery storage in LESs. The Agile contract has reduced export price during night and high export price during peak, following wholesale electricity price.

and power output capacity were 38,450 MWh and 2,744 MW [25], respectively. The state of charge at $t = 0$ was 50% of total pumped storage capacity. In the final time step, the pumped storage state of charge was equal to or more than the first time step.

C. *Retail contracts*

Several retail contract designs were compared in this study. The retail contracts used were based on real retail contracts offered by existing UK retailers. The schools existing retail contract consisted of a day and night price for imported electricity and no contract to sell excess electricity back to the grid. The remaining retail contracts were defined as follows:

- Octopus Fixed tariff – import and export prices were fixed for all times of the day.
- Bulb Smart tariff – export price was fixed. Import price was increased during peak hours (16:00-19:00).
- Octopus Go – import price was reduced at night (00:00-04:00). No export price was permitted with this contract.
- Octopus Agile – import and export prices tracked wholesale electricity price.

The Octopus Agile price was calculated by multiplying the wholesale electricity price by a factor, then increasing the price during peak hours. Customers would receive prices the prior evening so could plan energy used for the following day. For more information on the Octopus Agile tariff, refer to [30]. All other contracts were fixed time-of-use tariffs. The retail contracts are shown in Fig. 5 and Fig. 6.

IV. Results and Discussion

A benchmark case was defined in which the *Centralised* optimisation approach was used to minimise the operational cost of the NPS and LESs considering no battery storage in the schools. The total operational cost of the NPS for the benchmark case was £7.541 million. The NPS operating cost was the sum of generation cost in the power system. For the existing retail contract, the LESs operating cost for the benchmark case was £275,011, equating to a cost of £5.50 per school.

A. *Operation of battery storage*

The operation of the NPS and LESs with battery storage were modelled using the *Centralised* optimisation approach and *Bilevel* optimisation approach. For different approaches, the change in the operating costs of NPS and LES compared to the benchmark are shown in Fig. 7. The results from the *Centralised* optimisation approach shows that while installing battery storage in LESs reduces the operating cost of the NPS, the operating costs of the LESs increases. LES operating cost was calculated as the difference between the cost of importing energy and the revenue from exporting energy. LES operating cost was not explicitly considered in the *Centralised* optimisation approach but was calculated outside the optimisation, by multiplying import/export power values by the retail price. In reality, direct control contract would ensure the LESs benefit from allowing centralised control of their battery storage system. This result shows that centrally operated distributed battery storage systems can financially benefit the NPS. In the *Centralised* optimisation, the benefits for the LESs are limited by the terms of the direct control contract and retail contract.

Bilevel optimisation is a method used to explicitly consider the objectives of the LESs. The change in NPS and LES operating cost from the benchmark (with no battery storage) to the *Bilevel* optimisation approach (with battery storage) is shown on the right-hand side of Fig. 7. When the LESs operate their battery storage according to their objective, they can lower their operating costs in comparison to the benchmark (with no battery storage). Although, reducing their own costs results in an increase in the NPS operating cost. This result shows that where distributed battery storage systems are operated independently, they can have a negative impact on the NPS. This result is in agreement with previous comparisons of *Centralised* and *Bilevel* optimisation approaches [8], [13], [14].

To further highlight the impact of considering the distributed battery storage operating objectives, the change in wind curtailment is shown in Fig. 8. Where both are compared to the benchmark case. Fig. 8 shows that centrally operated distributed battery storage systems can reduce curtailed wind energy in the NPS. In contrast, distributed

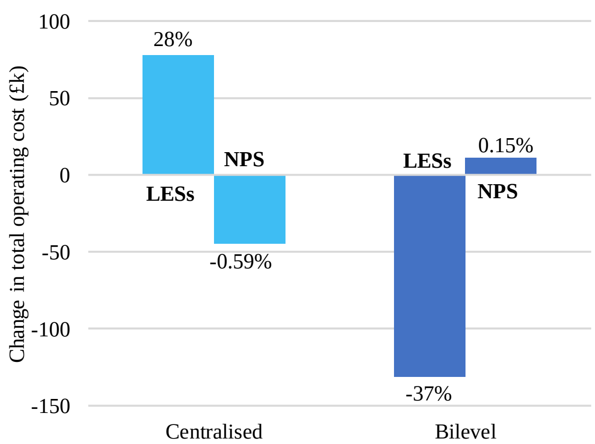

Fig. 7. Changes in operating cost from the benchmark to the *Centralised* optimisation (with battery storage) for all LESs and the NPS (left). As well as the changes in total operating cost from the benchmark to the *Bilevel* optimisation (with battery storage) for all LESs and the NPS (right). LES operating cost was found outside of the *Centralised* optimisation, by multiplying import/export powers with retail prices.

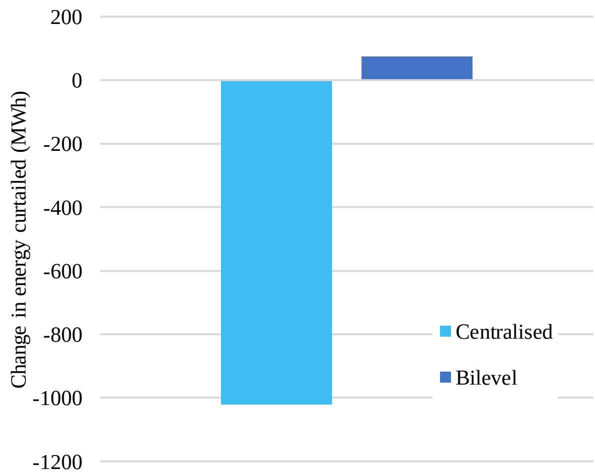

Fig. 8. Change in total curtailed wind energy over the 24-hour time horizon, relative to the benchmark case, shown for *Centralised* (light blue) and *Bilevel* (blue) optimisations. Comparison is made using the existing retail contract.

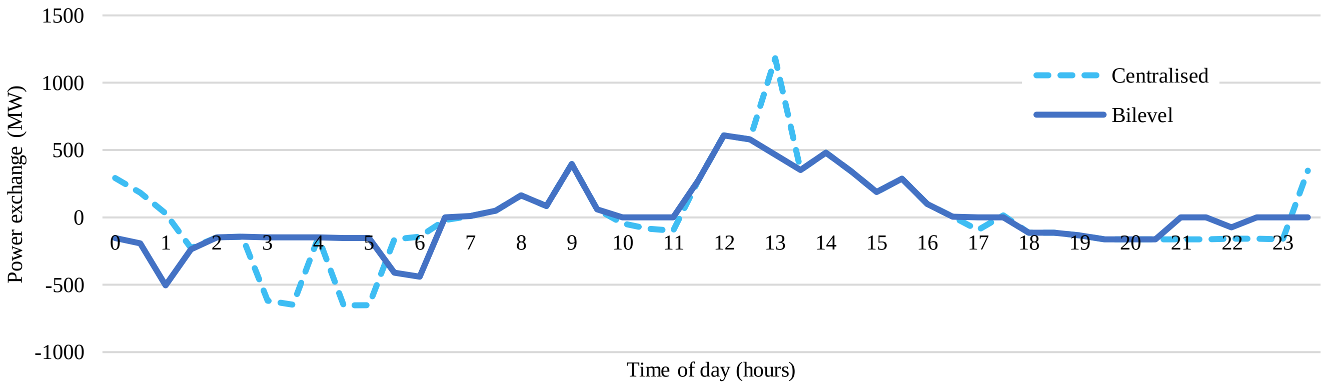

Fig. 9. Power exchanged between the NPS and LESs over a 24-hour time horizon, shown for the *Centralised* optimisation (light blue, dashed) and the *Bilevel* optimisation with the Octopus Agile retail tariff (blue, solid). Power exported from the LES to the NPS is shown as positive values and the power imported from the NPS to the LES is shown as negative.

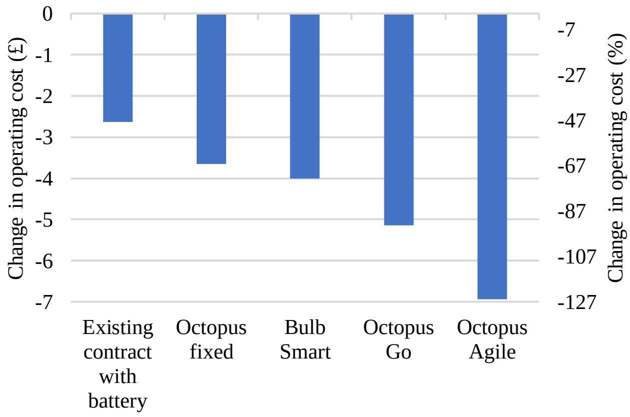

Fig. 10. Changes in operating cost of a single school for the 24-hour time horizon. These bilevel optimisation results are relative to the benchmark case with the existing retail contract and no battery storage.

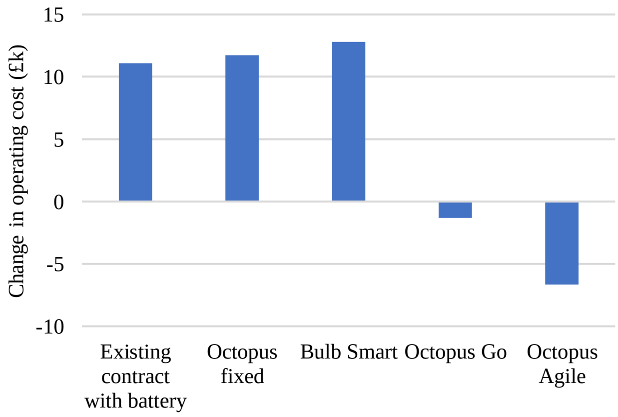

Fig. 11. Change in NPS operating cost for the 24-hour time horizon. These *Bilevel* optimisation results are relative to the benchmark case with the existing retail contract and no battery storage.

battery storage operated by its local owners can lead to an increase in curtailed wind energy. This negative impact on the whole system is due to a lack of coordination between the operation of the distributed battery storage and the NPS. This too demonstrates the objectives of the distributed battery storage system operator must be accounted for when investigating the whole system impacts.

Fig. 9 shows the power exchange between the NPS and the LESs, for the *Centralised* and *Bilevel* optimisation approaches with the Octopus Agile retail tariff. Power exported from LESs to the NPS is shown as positive and power imported from the NPS to the LESs is shown as negative. The results shown in this figure demonstrate the difference in operating behaviours of LESs in the *Centralised* and *Bilevel* optimisation approaches. From 00:00-01:00, the LESs export power in the *Centralised* approach and import power in the *Bilevel* approach. In addition, for periods 10:00-11:00 and 16:30-17:30, the LESs import power in the *Centralised* approach and have no power exchange in the *Bilevel* approach. Finally, in period 21:00-23:00, the LES imports power in the *Centralised* approach and imports significantly less power in the *Bilevel* approach. These results show that the *Centralised* approach does not account for the import/export costs/revenue for the LES. Whereas the *Bilevel* approach does, and therefore reduces import power instead of exporting, as the export price is lower than import price. The result shows that in the *Bilevel* approach, the LESs operate according to their own objectives.

To realistically quantify the benefits of distributed battery storage systems, their independent objectives must be explicitly considered. The *Centralised* approach maximises the benefits for the whole power system. Nevertheless, this may not accurately represent the strategic decisions of the distributed battery storage owners and can lead to exaggerated estimates of distributed battery storage value to the NPS. The *Bilevel* result is sub-optimal for the whole system. Though, its purpose is to improve the representation of distributed battery storage system objectives.

B. *Value of distributed battery storage*

In view of the discussion in the previous section, this section assesses the influence of retail contracts on the value of distributed battery storage systems for their owners and the NPS. Notably, the value of distributed battery storage is two-fold. It can provide reduced energy import costs and increased PV self-consumption for the schools. It can also reduce reliance on fossil fuel based technologies for the NPS, leading to lower generation cost and minimising renewable curtailment [6], [8].

To understand the value of battery storage for the school, several retail contracts were compared with the benchmark case. The *Bilevel* optimisation was used to produce the results shown in Fig. 10. This figure shows that the addition of battery storage results in a reduction in the cost of meeting electricity demand for the school, regardless of the retail contract. Although, the retail contract does have an impact on the level of cost savings and therefore on the value of the battery storage for the school. Introducing a battery storage system without changing the existing retail contract resulted in the smallest reduction in operating cost. Whereas the Octopus Agile tariff resulted in the highest operating cost reduction for the school. This contract provides prices for import and export electricity that track the wholesale electricity price. Higher variations in price allow the school to store cheap energy and export while the price is high.

While battery storage reduced the operating costs for the school, high penetrations of distributed storage can impact the NPS in different ways, depending on the retail contract. The *Bilevel* optimisation was used to investigate the impacts of distributed battery storage systems on the operating cost of the NPS, shown in Fig. 11. The figure shows the change in the NPS operating cost relative to the benchmark case. Three of the retail contracts caused an increase in NPS operating cost. The addition of a battery storage system without changing the existing contract resulted in the largest increase in operating cost for the NPS. Although some contracts increase the NPS operating cost, Octopus Go and Octopus Agile resulted in a reduction in the NPS operating cost. These results show that the retail contract design can impact the operating costs for the distributed battery storage owner but also the impact they can have on the NPS operating cost. The fixed retail contract creates no incentive for the distributed battery storage to be operated in line with NPS objectives. They simply encouraged the self-consumption of PV generation to reduce operating cost. The fixed time-of-use tariffs (Bulb Smart Tariff and Octopus Go) encourage the distributed battery storage operator to shift their demand to off peak times. This can reduce NPS operating cost, as cheaper generating technologies can be used to meet low demand. However, as the Bulb Smart Tariff shows, these contracts are fixed and may not always reduce NPS operating cost. In addition, they can lead to peaks at different times of the day/night. The Octopus Agile tariff tracks the wholesale electricity price, allowing the coordinated operation of distributed battery storage and the NPS. This tariff encourages the LES to shift demand from high-cost times to low-cost times, depending on the actual available generation in the power system. The result demonstrates that distributed battery storage can be beneficial or detrimental to the operating cost of the NPS. Retail contract design can influence their behaviour, facilitating the alignment of their objectives with the NPS.

V. Conclusion

This paper aimed to quantify the realistic value of distributed battery storage. Two approaches for integrated modelling of distributed battery storage and national power system interaction were compared. The first approach, termed '*Centralised* Optimisation', assumed centralised control of battery storage operation. The other approach, termed '*Bilevel* optimisation', explicitly considered the objectives of the battery storage system owners. A comparison between the approaches showed the *Centralised* operation of distributed battery storage reduces the national power system operating cost. In contrast, including the stakeholder objectives resulted in reduced energy costs for the schools and an increase in the national power system operating cost. This result highlights the importance of accounting for the objectives of the distributed storage operator when assessing its system wide benefits.

The impact of retail contracts on the value of distributed battery storage was also assessed. Several pre-determined retail contracts were compared. The introduction of battery storage allowed the school to reduce their energy costs for all retail contracts. On the contrary, some retail contracts increased the national power system operating costs, while others reduced them. This result demonstrates the influence that retail contract design can have on the value of distributed battery storage for both the stakeholders and the national power system.

A. Limitations and future works

The modelling and results presented in this paper have several limitations. Firstly, the use of 50,000 identical local energy systems limits the variability of their decision making. This assumption can be addressed through the introduction of a range of local energy system archetypes. Additionally, the modelling formulation does not account for battery degradation. Future work can integrate battery degradation constraints into the model. Furthermore, there is only one source of distributed flexibility (battery storage), which is not representative of the possible technologies available to provide distributed flexibility. To address this, the proposed *Bilevel* optimisation can include other technologies such as soft open points, thermal demand response, flexible loads and/or other energy storage technologies. Moreover, perfect coordination of local energy system flexibility is assumed. This neglects the impact of profit driven aggregators who would aggregate distributed power demand to participate in the wholesale electricity market. Future developments of the *Bilevel* optimisation can include an actor, such as a retailer or aggregator. Finally, all actors have perfect foresight of renewable generation and demand. To address this, uncertainties for renewable generation and electricity demands can be included.

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APPENDIX

In the *Bilevel* optimisation approach, the LES cost minimisation is the leader and the NPS cost minimisation is the follower. A common method for solving bilevel optimisations is by reformulating the bilevel model as a single level optimisation problem, using KKT conditions [31]. For any linear programming problem, a result that satisfies the KKT conditions, is guaranteed to be an optimal solution. Therefore, the KKT conditions that correspond to the follower optimisation can be formulated and included in the leading optimisation. This embeds the follower optimisation in the leading optimisation, guaranteeing an optimal solution for both problems, simultaneously. For the reformulation standard form, refer to [31].

The bilevel optimisation defined in equations (1)-(17) is reformulated and the following set of KKT conditions are defined.

$$K_j^{gen}\tau - \lambda_{t,j}^1 + \lambda_{t,j}^2 + \mu_t^1 = 0, \quad \forall t,j \in T,J \tag{18}$$

$$K^w\tau - \lambda_t^3 + \lambda_t^4 - \mu_t^1 = 0, \quad \forall t \in T \tag{19}$$

$$-\lambda_t^5 + \lambda_t^6 + \mu_t^1 + \tau\eta^{PS}\mu_t^2 = 0, \quad \forall t \in T \tag{20}$$

$$-\lambda_t^7 + \lambda_t^8 - \mu_t^1 - \tau\mu_t^2 = 0, \quad \forall t \in T \tag{21}$$

$$-\lambda_t^9 + \lambda_t^{10} - \mu_t^2 + \mu_{t+1}^2 = 0, \quad \forall t \in T \tag{22}$$

$$0 \le \lambda_{t,j}^1 \perp \left(P_{t,j}^{gen} - P_j^{min}\right) \ge 0, \quad \forall t,j \in T,J \tag{23}$$

$$0 \le \lambda_{t,j}^2 \perp \left(P_j^{max} - P_{t,j}^{gen}\right) \ge 0, \quad \forall t,j \in T,J \tag{24}$$

$$0 \le \lambda_t^3 \perp (P_t^w) \ge 0, \quad \forall t \in T \tag{25}$$

$$0 \le \lambda_t^4 \perp (P_t^{w\_max} - P_t^w) \ge 0, \quad \forall t \in T \tag{26}$$

$$0 \le \lambda_t^5 \perp \left(P_t^{PS\_ch}\right) \ge 0, \quad \forall t \in T \tag{27}$$

$$0 \le \lambda_t^6 \perp \left(P^{PS\_max} - P_t^{PS\_ch}\right) \ge 0, \quad \forall t \in T \tag{28}$$

$$0 \le \lambda_t^7 \perp \left(P_t^{PS\_dis}\right) \ge 0, \quad \forall t \in T \tag{29}$$

$$0 \le \lambda_t^8 \perp \left(P^{PS\_max} - P_t^{PS\_dis}\right) \ge 0, \quad \forall t \in T \tag{30}$$

$$0 \le \lambda_t^9 \perp (E_t^{PS}) \ge 0, \quad \forall t \in T \tag{31}$$

$$0 \le \lambda_t^{10} \perp (C^{PS} - E_t^{PS}) \ge 0, \quad \forall t \in T \tag{32}$$

The stationary constraints are defined in equations (18)-(22). They are derived from the first order derivatives of the Lagrangian function, with respect to the five decision variables of the follower optimisation problem ($P_{t,j}^{gen}$, P_t^w, $P_t^{PS\_ch}$, $P_t^{PS\_dis}$, E_t^{PS}). The complementary slackness constraints are defined in equations (23)-(32), where $0 \le a \perp b \ge 0$ is equivalent to $0 \le a, b \ge 0$ and $ab = 0$. The latter constraint makes these conditions non-linear. They are linearized using the Fortuny-Amat transformation [22]. This is when each complementary slackness condition, given by $0 \le a \perp b \ge 0$, can be replaced by the following:

$$0 \le a, 0 \le b, a \le MU, b \le M(1-U),$$

where M is a sufficiently large enough constant and U is a binary variable that corresponds to each complementary slackness variable. The bilevel optimisation problem has now been reformulated as a single-level, linear mathematical program with equilibrium constraints (MPEC). The final model is a single-level mixed-integer linear program (MILP), with the objective function defined in equation (1), subject to the constraints defined in (2)-(8), (11)-(17), (18)-(22) and the linear equivalents of (23)-(32).