Optimal Residential Battery Scheduling

I. Introduction

ELECTRIC grids are facing important challenges due to the increasing penetration of distributed intermittent generation and electricity consumption at a residential level caused by electric vehicles and electric-based heating systems like heat pumps. One solution for safe grid management is local battery storage, the cost of which is still high [1], and currently inhibiting battery adoption at individual household level. However, electrochemical battery costs are projected to fall, with the development of new products such as Tesla's Powerwall [2]. A key research area, in this context, is the development of smart battery control and scheduling that aims to optimize the revenues and services a battery can provide.

Motivated by the ReFLEX project [3], one of the largest smart energy demonstrators in the UK - running on the Orkney islands in Scotland, this paper focuses on the optimisation and control of residential batteries, which are coupled with a small renewable generator, such as rooftop solar PV or small wind turbines. The main purpose of such systems is the household provision with locally produced electricity and at a lower financial and carbon cost. A key objective of home batteries is the reduction of consumer electricity bills.

A battery control scheme consists of operational real-time decisions to charge or discharge the battery. Battery control can be informed by optimization and forecast techniques, generally called *optimisation-based control*, or by practical methods that do not guarantee optimality and can be called *heuristic control*. In this paper, we propose an optimisation-based control scheme with consideration of battery cycling cost for household prosumer applications and compare this with heuristic approaches.

Prior research work on optimal battery scheduling can be categorised into works that focus on the optimal scheduling algorithm problem formulation with the aim to optimize the end-user profits and by accounting for the battery lifespan and its depreciation, as in [4]–[7], where the battery cycles performed in the battery lifetime are considered, and works that focus on the optimization method itself, such as the use of evolutionary algorithms [8], [9].

This work focuses on the battery scheduling optimization with consideration of its lifespan in the optimization function. The optimization algorithm used in this work, is based on Mixed Integer Linear Programming (MILP), which makes the work easily replicable and implementable. The first contribution of the paper is the extension of the optimization problem formulation proposed in [5] and [7] and used in [4] and [6], such that the battery cycle life is included in the optimization problem. Next, we study the impact of optimal battery control with lifespan consideration on prosumer revenues and compare this with a heuristic control method and an optimization-based control without consideration of battery lifespan.

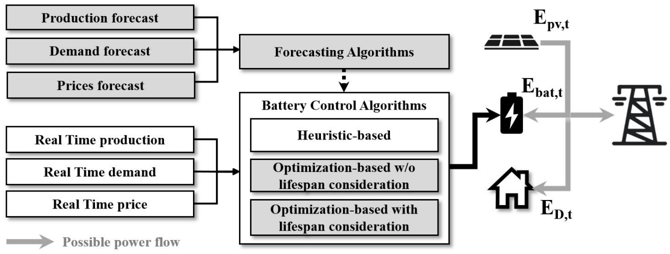

Fig. 1. Schematic of battery control algorithms used in this study

II. Battery Control Algorithms

In this section, we present two battery control algorithms, the operation of which will be compared with the optimization-based approach with lifespan consideration. Fig. 1 summarises the context of the study and shows that optimization-based control schemes rely on forecast algorithms of renewable production, demand and electricity prices. First, a heuristic control algorithm is presented that does not rely on forecasting algorithms. Next, we present an optimization-based control scheme without battery lifespan consideration.

A. Heuristic-Based Battery Control Algorithm

In the heuristic case, the control algorithm relies on `If... Then` rules, based on the difference between the household power consumption and the PV production. When the PV system exceeds the power demanded in the household, the heuristic control scheme charges the battery, until it reaches full capacity. Any excess is exported and sold to the main grid. When the demand exceeds the PV production, the battery is discharged, until it is empty. Any remaining deficit is purchased and imported from the grid. Note here that, decisions based on price considerations were not included in the heuristic method, as for the ToU electricity tariffs [10] assumed in this work, it did not demonstrate better revenues.

B. Optimization-Based Battery Control Algorithm without Lifespan Consideration

Here we present a battery control algorithm based on a MILP implementation of the optimization problem that determines the battery scheduling i.e. the charging or discharging power for every time step t, such that the prosumer electricity bill is minimized over a time horizon. The cost for using the battery is not considered in this control scheme. The problem can be formulated as a MILP optimization problem with the following parameters:

Variables: all variables are vectors of dimension N, where N corresponds to the number of time steps considered for optimization ($t \in [1, ..., N]$). For example, if the optimization is performed over one day and for half-hourly data, $N = 48$, hence, all variables will be constituted of 48 elements:

1) The energy imported from the grid $E^N_{Grid_{in}}$, where superscript N means that $E^N_{Grid_{in}}$ is a vector of N elements. Each element, noted $E_{Grid_{in},t} \in E^N_{Grid_{in}}$ corresponds to the energy imported from the grid at time t.
2) The energy exported to the grid $E^N_{Grid_{out}}$.
3) The energy exported from the battery when it discharges $E^N_{bat_D} \geqslant 0^N$. At times t when battery is not discharging, $E_{bat_D,t} = 0$.
4) The energy imported from the battery when charging $E^N_{bat_C} \geqslant 0^N$. At times t when the battery is not charging, $E_{bat_C,t} = 0$. Hence, $E^*_{bat_t} = E_{bat_D,t} - E_{bat_C,t}$.
5) Two auxiliary variables ξ^N_{in} and ξ^N_{out} are used to decorrelate $E^N_{Grid_{in}}$ and $E^N_{Grid_{out}}$.
6) Two binary variables α^N and β^N are used to ensure that the system cannot import from and export to the grid at the same time, i.e. $E_{Grid_{out},t}$ is equal to 0 when $E_{Grid_{in},t} \neq 0$, and vice versa.

Optimization function: the minimization optimization function that corresponds to the electricity bill is given as:

$$f = E^N_{Grid_{in}} \cdot BP^N - E^N_{Grid_{out}} \cdot SP^N \quad (1)$$

where $SP_{t\in[1,...,N]}$ is the electricity selling price at time t and BP_t is the electricity buying price at time t.

Inequality Constraints:

1) $E_{Grid_{in}} = 0$ when $E_{Grid_{out}} \neq 0$ and vice versa, which is ensured by the inequalities below:
$$\begin{aligned} 0 \leq E^N_{Grid_{in}} &\leq \alpha E^N_{max} \\ 0 \leq E^N_{Grid_{out}} &\leq (1-\alpha) E^N_{max} \end{aligned} \quad (2)$$
where E^N_{max} is a N elements vector equal to E_{max}, i.e. a maximum quantity of energy the household can inject to or consume by the grid.
2) Similarly:
$$\begin{aligned} 0 \leq \xi^N_{out} &\leq \alpha E^N_{max} \\ 0 \leq \xi^N_{in} &\leq (1-\alpha) E^N_{max}. \end{aligned} \quad (3)$$
3) The State of Charge (SoC) must not exceed the maximum battery capacity SoC_{max}:
$$\begin{aligned} \forall t \leq N, &\sum_{k=1}^{t} E_{bat_C,k} - \sum_{k=1}^{t} E_{bat_D,k} \\ &\leq SoC_{max} - SoC_0 \end{aligned} \quad (4)$$
where SoC_0 is the initial battery SoC. (4) is easily implemented in matrix formulation using triangular matrices.
4) SOC is always greater than the battery minimum capacity SoC_{min}, that must be taken equal to 0 in order to maintain the convexity of the problem, in which case $SoC_{max} = SoC^{real}_{max} - SoC_{min}$:
$$\begin{aligned} \forall i \leq N, &\sum_{k=1}^{t} E_{bat_D,k} - \sum_{k=1}^{t} E_{bat_C,k} \\ &\leq SoC_0 - SoC_{min} \end{aligned} \quad (5)$$
5) $E_{bat_D} = 0$ when $E_{bat_C} \neq 0$ and vice versa, which is ensured by the following equations:
$$\begin{aligned} 0 \leq E^N_{bat_D} &\leq \beta E^N_{bat_{max}} \\ 0 \leq E^N_{bat_C} &\leq (1-\beta) E^N_{bat_{max}}. \end{aligned} \quad (6)$$
where $E_{bat_{max}}$ is the maximum power from the battery (corresponding to the maximum C-rate).
6) Lower limit for each variable is 0.
7) Upper limits are equal to the maximum energy quantity E_{max} for $E_{Grid_{in}}, E_{Grid_{out}}, \xi_{in}, \xi_{out}$, 1 for the binary variables, and $E_{bat_{max}}$ for E_{bat_D} and E_{bat_C}.

Equality Constraints: the demand must be met at anytime:

$$\begin{aligned} E^N_{Grid_{in}} + \eta_d E^N_{bat_D} - \frac{E^N_{bat_C}}{\eta_c} - \xi^N_{in} &= E^N_D - E^N_{pv} \\ E^N_{Grid_{out}} - \eta_d E^N_{bat_D} + \frac{E^N_{bat_C}}{\eta_c} - \xi^N_{out} &= E^N_{pv} - E^N_D \end{aligned} \quad (7)$$

where η_d and η_c are the discharging and charging efficiencies of the battery, respectively.

The minimization of (1) provides the optimal battery schedule i.e. the charging $E^N_{bat_C}$ and discharging power $E^N_{bat_D}$ for N time steps of the time-ahead horizon. Once the battery schedule is obtained, we assume this will be implemented in real-time decisions. Any inaccuracies on demand or production forecasts, used to derive the optimal schedule, were not considered and are out of the scope of the paper.

In this section, we presented an heuristic-based and an optimization-based battery control algorithm based on the minimization of (1). In the following section, we propose an extension of (1) that includes the cost for using the battery.

C. Performance Comparison of Battery Control Algorithms

To assess the benefits of including the battery's lifespan consideration in the scheduling optimization problem, the household bills were compared in the four following cases (the time horizon in half-hourly time steps and average computing time for a daily schedule are shown in parenthesis):

1) **Heuristic-based control (0.2ms)**: in this case the prosumer implements the heuristic battery control algorithm introduced in section II.
2) **Optimization-based control without lifespan consideration for N=24 (0.1s)**: in this case the prosumer uses the optimisation-based algorithm described in section II, with $N = 24$ half-hourly time steps.
3) **Optimization-based control without lifespan consideration for N=144 (6.3s)**: identical to the previous case, with $N = 144$ half-hourly time steps.

4) **Optimization-based control with lifespan consideration for N=24 (29.9s)**: this last scenario implements an optimization problem not presented in the paper.

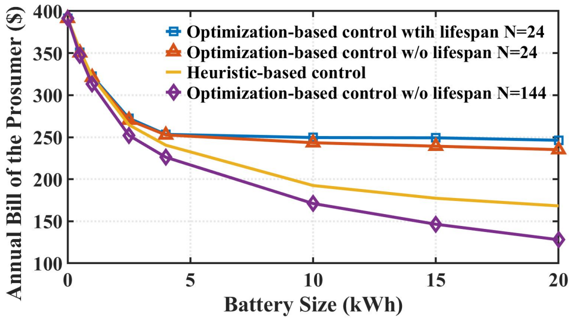

Fig. 2. Comparison of the annual bill achieved with the different control algorithms for batteries capacities ranging from 0 to 20 kWh.

Fig. 2 presents the annual bill for a prosumer in each of the proposed scenarios and different battery capacities.Fig. 2 shows that the lowest bill is obtained with the optimization-based algorithm without lifespan consideration and a long time horizon ($N = 144$, assuming a perfect forecast). The heuristic-based algorithm also demonstrates a significant reduction in the energy bill. The good performance observed is mostly due to the low selling (export) prices, which make discharging the battery always profitable, whenever there is not enough PV production. According to Fig. 2, the control algorithm with consideration of the battery lifespan does not provide as much benefit in terms of energy bill reduction, due to the small time horizon for the optimization. Further increase of the time horizon N, would lead to unrealistic computation time.

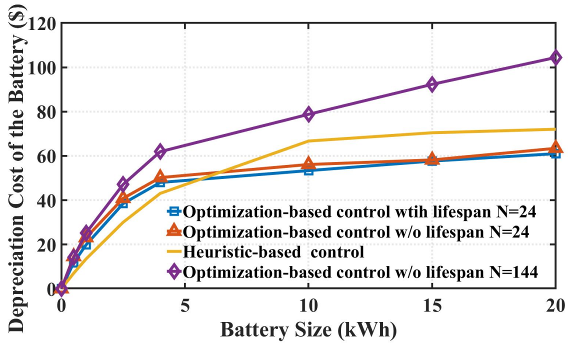

Fig. 3. Annual cost for the depreciation of the battery for the different control algorithms and for different battery capacities.

With regards to the optimization-based algorithm with lifespan consideration (Section III), we computed the annual depreciation cost of the battery, by use of the Rainflow algorithm [11]. Fig. 3 shows that the proposed scheme scheme, actually decreases the depreciation cost of the battery, but only by a small amount when compared to the approach without lifespan consideration, due to the smaller cost for battery cycling.

Note here that the comparison of the financial benefits between the optimal schedule with $N = 144$ and the heuristic-based approach must take into account the inaccuracies that would be introduced by imperfect forecasting.

III. Conclusions

Recent years have seen increasing interest in residential batteries as a means to reduce electricity bills for battery owners. In this paper, we introduced a new optimization formulation that integrates consideration of battery lifespan by accurately computing the DoD of each discharge half-cycle experienced by the battery. The proposed optimization problem includes the battery cycling costs in the optimization function, and is formulated such that it is solvable using a MILP technique. Results show that consideration of battery lifespan in the optimization algorithm does not necessarily yield to lower prosumer energy bills, when compared to other approaches, but it can lead to lower depreciation cost of the battery. Our results show a good performance for heuristic-based scheduling when export prices are lower than electricity import prices. Nevertheless, consideration of battery lifespan remains of great practical interest, because smart battery scheduling may lead to improved battery lifetime. Moreover, the performance needs to be studied for other emerging pricing schemes, such as in Peer-to-Peer markets or applications that provide grid frequency response services.

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