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Optimal Residential Battery Scheduling with Asset Lifespan Consideration

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***Abstract*—Recent development of renewable generation and increasing penetration of electric vehicles have led to large volumes of residential battery storage systems connected at distribution networks. In this paper, we propose a control algorithm for residential batteries that determines optimal day-ahead battery scheduling and operation with the aim to minimize household energy bills and in the context of dynamic Time of Use (ToU) electricity tariffs. The proposed formulation of the optimization problem takes into consideration the battery's depreciation cost, which is determined by the accurate enumeration of battery cycles, including partial cycling i.e. battery cycles that do not start or end at 100% of State of Charge (SoC). A key advantage of the proposed formulation is that the problem can be solvable by use of linear programming. In addition, we study and compare the benefits of the optimisation-based algorithm with lifespan consideration to a simple heuristic-based battery control scheme and an optimisation-based algorithm without battery lifecycle consideration. Results show that battery lifespan consideration in the optimization algorithm does not necessarily yield to lower prosumer energy bills, when compared to other approaches, but it can lead to a lower depreciation cost of the battery.**

***Index Terms*—Battery management system, distributed generation, linear programming optimization, smart grids**

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.

The structure of the paper is: Section II introduces a heuristic control method and an optimization-based control without considering battery lifespan, Section III proposes a new closed problem formulation for battery scheduling, which accounts for cycle costs and is compatible with MILP optimization, Section IV compares the operation of different battery control schemes, and finally Section V concludes on the relevance of the proposed method in the current market regime.

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

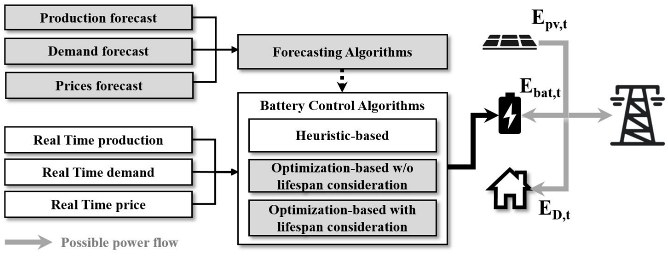

Fig. 1. Schematic of battery control algorithms used in this study

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:

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

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:
$$\begin{aligned} 0 \leq E^N_{Grid_{in}} \leq \alpha E^N_{max} \\ 0 \leq E^N_{Grid_{out}} \leq (1-\alpha) E^N_{max} \end{aligned} \tag{2}$$
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:
$$\begin{aligned} 0 \leq \xi^N_{in} \leq \alpha E^N_{max} \\ 0 \leq \xi^N_{out} \leq (1-\alpha) E^N_{max}. \end{aligned} \tag{3}$$
3) The State of Charge (SoC) must not exceed the maximum battery capacity SoC_{max}:
$$\begin{aligned} \forall t \leq N, \sum_{k=1}^{t} E_{bat_C,k} - \sum_{k=1}^{t} E_{bat_D,k} \\ \leq SoC_{max} - SoC_0 \end{aligned} \tag{4}$$
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 $SoC_{max} = SoC^{real}_{max} - SoC_{min}$:
$$\begin{aligned} \forall i \leq N, \sum_{k=1}^{t} E_{bat_D,k} - \sum_{k=1}^{t} E_{bat_C,k} \\ \leq SoC_0 - SoC_{min} \end{aligned} \tag{5}$$
5) $E_{bat_D} = 0$ when $E_{bat_C} \neq 0$ and vice versa, which is ensured by the following equations:
$$\begin{aligned} 0 \leq E^N_{bat_D} \leq \beta E^N_{bat_{max}} \\ 0 \leq E^N_{bat_C} \leq (1-\beta) E^N_{bat_{max}}. \end{aligned} \tag{6}$$
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}.

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Equality Constraints: the demand must be met at anytime:

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

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.

III. Optimization-Based Battery Control Algorithm with Lifespan Consideration

Useful battery lifetime depends on its usage. In this paper, we consider the impact of the number of charge/discharge cycles on the battery life. Useful battery life is usually specified for a given number of cycles at specific Depths of Discharge (DoD), after which the battery is assumed to have lost more than 20% of its initial capacity. Fig. 2 shows on the left side the number of cycles, noted N_{DoD}, that a battery cell can perform before the battery capacity B_{cap} reduces to 80% of its initial capacity, based on the data from [11]. The right side of Fig. 2 represents the cost of each cycle depth, noted C_{DoD}, obtained by taking the inverse of the number of cycles per DoD (N_{DoD}) and for a battery capacity B_{cap} of 10 kWh, with a price of 250$ per kWh for the battery cells [1].

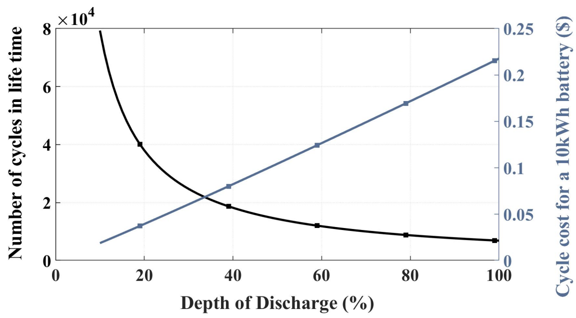

Fig. 2. Allowed number of cycles in a battery life time (right) and the cost associated with a cycle of a certain DoD for a 10 kWh battery, using a battery cost of 250$/kWh

The aim of this section is to extend the battery optimization problem described in Section II so it includes the cost of battery cycling in the optimization function. Research works in [5] and [7] propose an approach to include this cost in the optimization function. However, [5] does not consider cycles starting or ending at a SoC different than 100%, which makes it inappropriate for grid applications, and [7] does not explicitly compute the DoD of each cycle. Other well-known techniques used for extraction of partial cycling in fatigue data analysis, such as the Rainflow counting algorithm, cannot be used directly in the optimization problem, as they are not linear. Hence, this paper proposes an approach, that computes linearly the cost of each half cycle experienced by the battery. For clarity, only the DoD computation for discharging half-cycles will be described, but an equivalent procedure is also valid for charging cycles. The problem formulation is:

Variables: in addition to the variables introduced in Section II, the following variables are required:

1) $A^N = [A_1, ..., A_N]$, such that $A_{t\in[1,...,N]} = SoC_t$ for all t that correspond to a battery's change of status i.e. from charging to discharging. For all t when there is no status change, $A_t = 0$.
2) B^N, similar to A^N, $B_t = SoC_t$ when the battery status changes from discharging to charging.
3) C^N is a variable equal to the SoC at the beginning of the current discharging half cycle. The value remains for the whole duration of the discharge. For example, if a discharging half cycle starts at $t = t_1$ and ends at $t = t_2$, then $A_{t_1} = SoC_{t_1}$, and $C_t = A_{t_1} \forall t \in [t_1, ..., t_2]$, and $C_t = 0$ otherwise, until the next discharging cycle starts.
4) D^N is such that D_t is equal to the DoD of the discharging half cycle once it is complete. Similarly to the previous example, $D_{t_2} = SoC_{t_1} - SoC_{t_2}$, and $D_t = 0$ otherwise.
5) Two binary variables a^N and b^N such that $a_t = 1$ when a discharging half cycle starts, $b_t = 1$ when a discharging half cycle ends, and $a_t = b_t = 0$ otherwise.

Optimization function: the optimization function now integrates the cost of each half cycle. When only discharging cycles are considered, (1) becomes:

$$
f = E^N_{Grid_{in}} \cdot BP^N - E^N_{Grid_{out}} \cdot SP^N + D^N \cdot \frac{s}{2} \cdot \frac{100}{B_{cap}} \tag{8}
$$

where s corresponds to the slope of a linear interpolation that fits the battery cost per cycle curve showed in Fig. 2. Note that for some battery technologies, the cycle cost curve might not be linear, in which case a piecewise linear approximation can be used as in [5] and [7].

Inequality Constraints:

1) β^N (introduced in the previous section) needs to keep the same value within a discharging half-cycle, hence:

$$
\begin{aligned}
\forall t, -E_{bat_C,t} - \beta_t + \frac{1}{M}\beta_{t-1} \leq 0 \\
-ME_{bat_D,t} + \beta_t - \beta_{t-1} \leq 0
\end{aligned}
\tag{9}
$$

where M is a large coefficient compared to the energy quantities involved in the system.

2) To ensure that a^N represents a status change, from charging to discharging:

$$
\begin{aligned}
\forall t, \beta_t - \beta_{t-1} \leq a_t \\
a_t - \frac{1}{2}(\beta_t - \beta_{t-1}) \leq \frac{1}{2}.
\end{aligned}
\tag{10}
$$

3) Similarly for b^N:

$$\begin{aligned} &\forall t, \beta_t - \beta_{t-1} + b_t \geq 0 \\ &b_t + \frac{1}{2}\left(\beta_t - \beta_{t-1}\right) \leq \frac{1}{2}. \end{aligned} \tag{11}$$

4) Constraints for A^N so that A_t takes the SoC value when a discharging cycle starts:

$$\begin{aligned} &A^N - M \cdot a^N \leq 0 \\ &\forall t, \sum_{k=1}^{t-1} E_{bat_D,k} - \sum_{k=1}^{t-1} E_{bat_C,k} + A_t \leq SoC_0 \\ &\sum_{k=1}^{t-1} E_{bat_C,k} - \sum_{k=1}^{t-1} E_{bat_D,k} - A_t + M \cdot a_t \leq M - SoC_0. \end{aligned} \tag{12}$$

5) Similarly for B^N:

$$\begin{aligned} &B^N - M \cdot b^N \leq 0 \\ &\forall t, \sum_{k=1}^{t-1} E_{bat_D,k} - \sum_{k=1}^{t-1} E_{bat_C,k} + B_t \leq SoC_0 \\ &\sum_{k=1}^{t-1} E_{bat_C,k} - \sum_{k=1}^{t-1} E_{bat_D,k} - B_t + M \cdot b_t \leq M - SoC_0. \end{aligned} \tag{13}$$

6) Constraints for S^N are listed below:

$$\begin{aligned} &A^N - S^N \leq 0 \\ &S^N - M \cdot \beta^N \leq 0 \\ &\forall t, M\left(\beta_t - 1\right) \leq S_t - S_{t-1} \leq M\left(1 - \beta_{t-1}\right) \\ &S_t - A_t - M \cdot \beta_{t-1} \leq 0. \end{aligned} \tag{14}$$

7) Finally, to ensure that D^N represents the DoD at the end of every discharging half-cycle:

$$\begin{aligned} &D^N - M \cdot b^N \leq 0 \\ &\forall t, B_t - S_{t-1} + D_t \leq 0 \\ &S_{t-1} - D_t - B_t \leq M\left(1 - b_t\right). \end{aligned} \tag{15}$$

Equality Constraints: an additional equality constraint is required to include the DoD of the last half-cycle, in the case that the time horizon N is reached before the end of the discharging half-cycle:

$$\sum_{k=1}^{N} E_{bat_D,k} - \sum_{k=1}^{N} E_{bat_C,k} + D_N + S_{N-1} = SoC_0. \tag{16}$$

The same process is followed to include the cost of charging half-cycles. The MILP optimization problem with the objective function in (8), subject to the constraints given by (2)-(7) and (9)-(16) optimizes the battery scheduling and takes into account the cost of each half-cycle.

In the next section, the proposed formulation is validated by verifying that it captures the cycling cost of the battery and next the method is compared to the battery control schemes presented in Section II.

IV. Assessment of Optimal Scheduling with Battery Lifespan Consideration

To validate and assess the performance of the proposed control scheme, we applied it to a prosumer application consisting of a solar PV system, a battery storage and a household, as shown in Fig. 1. Half-hourly consumption and production data of a real household participating in the ReFLEX demonstrator project [3] were used, along with dynamic ToU tariffs from [10] for electricity prices. Note that the household electricity selling (export) prices are lower than the buying (import) prices. The analysis was performed for a duration of one week, then the results were extrapolated for the duration of one year. Simulations were run on Matlab on a 1.7GHz processor, using MOSEK solver with CVX for the MILP optimization.

A. Validation of the Proposed Optimization Formulation

Fig. 3 displays the prosumer's consumption and production results, along with the battery energy quantities derived by the optimization-based algorithm proposed in Section III. The lower part of the graph shows the battery SOC and the variable D, that represents the DoD of each discharging half-cycle. Fig. 3 shows that the proposed optimization formulation successfully computes the DoD for each discharging cycle, which it is then included in the optimization function.

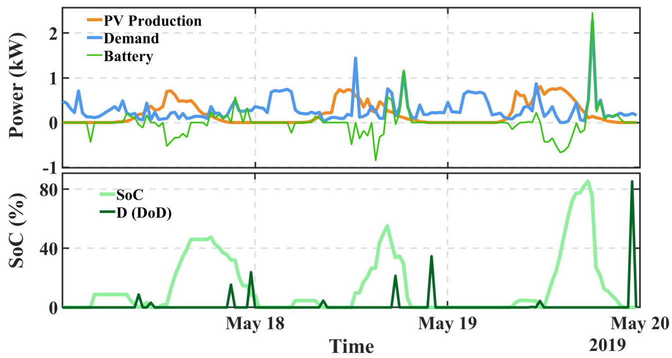

Fig. 3. Example of optimization outputs, with the variable D accurately capturing the DoD of each discharging half-cycle.

B. 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 the optimization problem formulated in section III, with $N = 24$ time steps.

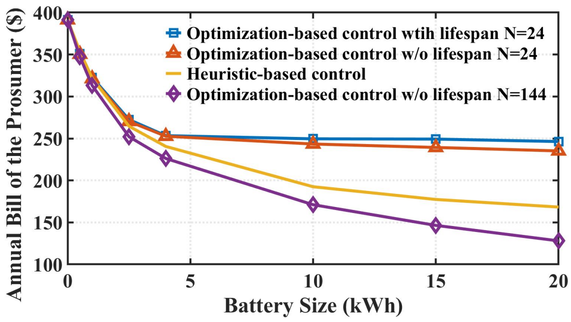

Fig. 4. Comparison of the annual bill achieved with the different control algorithms for batteries capacities ranging from 0 to 20 kWh.

Fig. 4 presents the annual bill for a prosumer in each of the proposed scenarios and different battery capacities.Fig. 4 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. 4, 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.

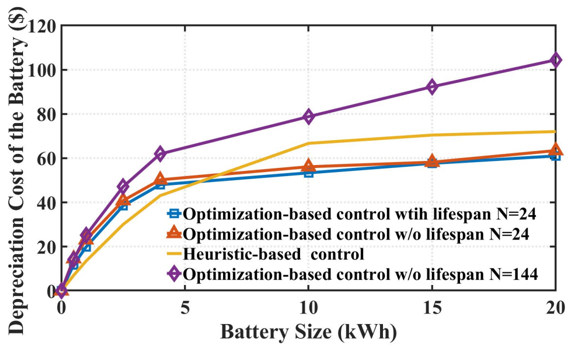

Fig. 5. Annual cost for the depreciation of the battery for the different control algorithms and for different battery capacities.

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 [12]. Fig. 5 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.

V. 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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