Improved Forecasting-Based Battery Energy Management Strategy for Prosumer Systems

Mercedes Ruiz-Cortés
Electrical, Electronic and Control Engineering Department
University of Extremadura
Badajoz, Spain
meruizc@peandes.es

Eva González-Romera
Electrical, Electronic and Control Engineering Department
University of Extremadura
Badajoz, Spain
evagzlez@unex.es

Rui Amaral Lopes
Electrical Engineering Department
University Nova de Lisboa,
Monte de Caparica, Portugal
rm.lopes@campus.fct.unl.pt

Enrique Romero-Cadaval
Electrical, Electronic and Control Engineering Department
University of Extremadura
Badajoz, Spain
eromero@unex.es

João Martins
Electrical Engineering Department
University Nova de Lisboa
Monte de Caparica, Portugal
jfmartins@fct.unl.pt

María Isabel Milanés-Montero
Electrical, Electronic and Control Engineering Department
University of Extremadura
Badajoz, Spain
milanes@unex.es

Fermín Barrero-González
Electrical, Electronic and Control Engineering Department
University of Extremadura
Badajoz, Spain
fbarrero@unex.es

Abstract—**This work presents an energy management strategy based on scheduling battery operation in prosumer systems, according to forecast data available 24 hours in advance. The proposed method seeks to reach a beneficial compromise between prosumers and distribution grid operators, independently of specific economic context or technical regulations. An improvement to deal with forecast inaccuracy is carried out. Results demonstrate that it offers good properties regarding energy management, with a stored energy reserve estimation, battery lifetime preservation and self-consumption and self-sufficiency enhancement.**

Keywords—battery energy management, battery setpoints scheduling, forecast error, prosumer system, self-consumption, self-sufficiency

I. Introduction

Combating climate change is one of the main challenges that the world must carry out currently. This worrisome issue has led to the European Commission to pose more and more ambitious targets regarding greenhouse gas emissions reduction, renewable energy sources share increase and energy efficiency improvement, with the additional objective of reaching a higher energy independence [1]. Authorities put the aforementioned goals in their agendas and different energy directives were developed in each country.

There is a consensus about the importance of reducing energy consumption in households, without detriment to lifestyle comforts. Consumers are encouraged to optimize their energy usage putting in practice Demand Side Management (DSM) strategies, based on Demand Response (DR) programs, local renewable generation or energy storage among others [2]. Photovoltaic (PV) generation has succeeded over other renewable technologies in residential sector, allowing small consumers become prosumers (producers + consumers). PV systems combined with batteries – particularly Li-ion based – as storage device seems to be one of the most accepted options in research and industry. However, high investment costs related batteries mean an encumbrance to its real spread. In this context, designing optimal energy management strategies to launch their use is a fundamental task for researchers.

In this line, several approaches have been developed, focused on charging/discharging the battery following instantaneous PV surplus or scheduling its operation in advance pursuing different objectives [3]-[8]. Most of them consider, and even advocate, feed-in limit regulations to deal with disturbances caused by PV grid injections, which is a problem from the distribution grid operator perspective [6]. The preferred objective is generally to maximize economic profits, but in the last years many countries have modified feed-in tariffs to promote self-consumption [7], [8], whereas others have toughened self-consumption regulations in monetary terms [9]. In this complex situation with divergent and changeable energy policies, energy management strategies are not easily applicable to whichever scenario. Furthermore, battery scheduling strategies have to handle forecast errors, which can ruin the obtained energy plan [3], [5]. Proposals to correct them are made in some cases [4].

The motivation of this work relies on the aforesaid challenges. It presents a procedure to plan 24 hours ahead the charge/discharge battery setpoints of one individual prosumer with the purpose of achieving benefits for prosumer and grid operator simultaneously. The framework is valid for most scenarios, since it is less sensitive to volatile energy policies in terms of economic incentives or technical regulations. In addition, an improvement of the scheduling algorithm is suggested to mitigate the impact of forecast errors in computed setpoints and carry out a more effective battery energy management. Despite the case studied here represents a residential prosumer, the proposed technique is also valid for industrial or services prosumers. The paper is structured as follows: Section II describes the prosumer system taken as a case study. Section III explains the proposed method to schedule the battery operation and deal with forecast inaccuracy. In Section IV, the obtained simulation results are shown and discussed. The paper finishes summarizing the main conclusions in Section V.

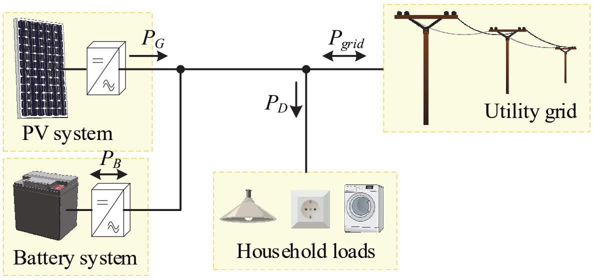

Fig. 1. Household energy system configuration.

II. Case Study

The planning strategy proposed in this paper has been designed to be applied in a prosumer household connected to the utility grid, with renewable generation and storage units. The selected configuration is illustrated in Fig. 1. It is composed by typical household loads, a PV installation and a Li-ion battery as energy storage equipment. An AC topology, with independent inverters for the PV array and the battery was chosen due to its higher level of flexibility and its capability to be easily implemented in PV systems previously installed without storage, instead of replacing the existing PV inverter if a higher size is required [5], [7]. Anyway, the proposed strategy is also applicable in a DC coupled system.

For the specific case studied here, the maximum expected generated and demanded power in the dwelling is in the range of 5-6 kW. The PV array is coupled to an inverter with an average efficiency of 90%. The battery was modelled following the specifications of the commercially available Li-ion NMC battery BMZ ESS 7.0. For the battery charger characterization, SMA Sunny Island 4.4 was considered due to its compatibility with the selected battery model. Table I collects the battery system parameters used for the simulation.

TABLE I. Battery System Parameters

Parameter	Value
Battery nominal capacity, Q_{nom} (kWh)	6.74
Battery usable capacity, Q_{us} (kWh)	5.39
Depth of discharge, *DoD* (%)	80
Charge/discharge battery efficiency, η_B (%)	95
Nominal charger power, $P_{charger}$ (kW)	3.3
Charger efficiency, $\eta_{charger}$ (%)	95.5

III. Forecast Based Battery Management Method

This paper presents a battery management strategy based on the scheduling of the energy that the battery provides or stores for the next 24 hours from the time in which the planning is done. 1-hour resolution was chosen as scheduling time step, which is sufficient for smoothing low disparities in the prosumer generation-demand balance, whereas fast variations are compensated by the utility grid. The selected time horizon and sample time emulates the planning carried out by day-ahead spot markets, based on estimated electricity production and consumption. The solution of the battery scheduling at each time step are the setpoints that the battery has to follow hour by hour the next day. Since the charge/discharge of the battery is programmed 1 day ahead, forecasting data are required to calculate it. Therefore, having accurate forecasts in advance is key to obtain a battery dispatch program that fits properly behind actual conditions and complies with the desired operating goals.

A. Charge/Discharge Decision Making Procedure

The objective function implemented in this work aims to minimize the mismatch between the renewable generation (P_G) and the electricity consumption (P_D) of the prosumer residence over the next 24 hours, using the battery capacity to shift generation/consumption excess. The battery acts as a power source/sink when there is an electricity consumption/production surplus, in a way that changes the initial demand profile into a new one more similar to the generation shape. The modified demand profile ($P_{D,mod}$) is calculated for each 1-hour time interval as

$$P_{D,mod}^{i} = P_{D}^{i} + \eta_B \eta_{charger} P_{B}^{i}, \tag{1}$$

where η_B and $\eta_{charger}$ are the battery and the battery's converter efficiencies respectively, introduced to account the losses in the battery system. P_B^i is the battery setpoint for the hour *i*, determined by the objective function

$$\text{minimize } f_{mismatch} = \sum_{i=1}^{24} \left(P_{D,mod}^{i} - P_{G}^{i} \right)^2 . \tag{2}$$

Note that $P_B^i > 0$ means charge and $P_B^i < 0$ means discharge; in case that $P_B^i = 0$ the battery is idle. P_G^i includes the PV system's losses. Energy imbalances between $P_{D,mod}^i$ and P_G^i are taken over the distribution grid, with hourly and subhourly resolution:

$$P_{grid}^{i} = P_{G}^{i} - P_{D,mod}^{i} . \tag{3}$$

The mismatch minimization target has been preferred before others more usual in the literature, such as minimization cost or peak shaving, because it constitutes a compromise between the prosumers and the distribution system operator interests. On one hand, the distribution system operator seeks to ensure grid stability, avoiding uncontrolled power injection that causes overload. On the other hand, the prosumers' goal is to achieve economic profits in their electricity bills.

Although in some countries a welfare situation was reached with feed-in tariffs, in other cases payments and incentives are decreasing or simply do not exist, whereas electricity prices continue increasing. To face this situation, prosumers are aimed to self-consume their own production to supply their demand and, therefore, rise their self-sufficiency with respect to the distribution grid. This implies a reduced prosumer-grid interaction, which is precisely what the mismatch minimization gets. In this way, the distribution system operator attains a more stable functioning, and prosumers benefit from lower energy purchases. It is true that the proposed objective function does not necessary provide the better solution in terms of economic profits for prosumers, since it does not consider hourly electricity prices. However, it affords a general scenario unaffected by the diversity of regulation policies. Moreover, it is especially suitable for places where feed-in limit is not considered and, thus, prosumers may not have generation curtailment control.

In addition to the defined objective function, the resulting battery hourly setpoints must accomplish a set of technical specifications that guarantees a safe operation and helps to preserve the battery lifetime. These considerations have been formulated as the following constraints:

- The output power of the battery system (charging or discharging) at the i-th time slot cannot exceed the nominal power of the battery charger. Also, in this work straight energy transfer between battery and distribution grid is not allowed to restrict prosumer-grid energy trades, in accordance with the objective function. Consequently, the battery only can charge or discharge the generation or demand excess respectively. Both previous conditions are satisfied by (4).

$$\begin{aligned} P_B^i &\geq \max\left(-P_{charger}, P_G^i - P_D^i\right) \text{ if } P_G^i < P_D^i \\ P_B^i &\leq \min\left(P_{charger}, P_G^i - P_D^i\right) \quad \text{if } P_G^i \geq P_D^i \end{aligned} \tag{4}$$

- The state of charge (SoC) of the battery at the hour i (SoC^i), defined as the ratio between the energy stored at that hour and its usable capacity (Q_{us}), cannot surpass the range 0–100%. Note that SoC^i is referenced to usable capacity instead of nominal capacity (Q_{nom}). Considering that $Q_{us}/Q_{nom} = DoD$, this limitation ensures that the maximum depth of discharge recommended by the manufacturer is respected and the battery does not suffer overcharge or overdischarge. Therefore, each P_B^i value must satisfy

$$0 \leq P_B^i \Delta t / Q_{us} + SoC_{init}^i \leq 100\,, \tag{5}$$

where Δt is the computation granularity (1 hour) and SoC_{init}^i is the initial SoC of the battery at the beginning of the hour i.

- To avoid discontinuities in the scheduling problem solution, the initial SoC of the battery at the i-th hour must be the same as the final SoC at the previous hour, i.e,

$$SoC_{init}^i = SoC_{final}^{i-1}\,. \tag{6}$$

- The battery setpoints between consecutive hours cannot differ more than a determined amount ΔP_B in absolute terms (i.e. charging or discharging),

$$\left|P_B^i - P_B^{i-1}\right| \leq \Delta P_B\,. \tag{7}$$

This means that the hourly SoC variation is limited, in order to prevent sharp charges or discharges that cause battery stress and accelerated cycle aging. Here, the power gradient is 1 kW, which implies a maximum hourly SoC change about 18.5%.

Because of its easy implementation and good performance, genetic algorithms were selected to decide the amount of energy that the battery must charge or discharge each hour on a daily basis according to the rules explained before. The *ga*() function provided by MATLAB® was employed as optimization tool to solve the planning problem.

B. Forecast Errors Dealing

Notice that the battery management strategy described in Section III.A is carried out 24 hours in advance based on 1-day ahead renewable generation and electricity consumption forecast. As a result, the quality of the daily battery dispatch solution strongly depends on the accuracy degree of the predicted data.

PV generation is characterized by intermittent and uncontrollable behavior, and it relies on weather variables such as irradiance and temperature. An accepted range of global error on daily PV production is 10–20%, which is not very high, but differences between forecasted and real PV generation profiles are expected [10]. In the case of electricity load forecasting, good accuracy is achieved for aggregated consumers at the level of substations (1–2%), but at the individual household level the error may rise from 20% to 100% or even more, depending on several factors that modify the electricity consumption pattern of the specific dwelling [11].

Considering these guidelines, forecasted generation and demand profiles were created multiplying actual recorded data by a random vector of 24 elements (one per daily hour). Each element represents the deviation between related hourly forecasted and real values. The possible deviation to apply is limited to a range that increases as the corresponding hour is farther, trying to mimic the fact that uncertainties rise for more distant interval times. The maximum range considered for generation random vector goes from 40% to 70% hour by hour, whereas it goes from 70% to 100% for the demand random vector. Remark that these ranges mean the highest possible deviations with respect to actual values, so forecasted demand for the hour i-th may be only 10% lower than its corresponding real value, e.g. To tackle forecast errors, a “proactive” approach carried out hour to hour (h2h) is assessed in contrast to the more “passive” strategy explained up to here, executed only day to day (d2d). Fig. 2(a) schematizes the differences between both approaches.

The so called “passive” management method runs the charge/discharge decision making procedure exposed in Section III.A once a day using available forecasts, and fixes the battery operation over the next 24 hours. Shortly before the last programmed hour, new forecasted results are collected and the genetic algorithm is run again to plan the new day. This strategy is heavily vulnerable to unexpected changes in generation and consumption predictions, especially at the last hours of the day, when forecast uncertainties are higher. In this situation, it may occur that the scheduled battery dispatch would not be valid and an energy balance disparity occurs between PV system, loads, battery system and grid.

The “proactive” strategy leads with forecast errors following the same routine and rules as the previous one but updating hour to hour. As starting point, at hour $i = 0$, it uses available forecast profiles as input data to compute the best operation over the next 24 hours, i.e., $P_B^1, P_B^2, \ldots, P_B^{24}$. However, this first result is not the definitive daily schedule, but it is a prearrangement that provides the setpoint to the hour immediately after the algorithm execution, P_B^1. One hour later, at hour i = 1, new 24-hour ahead forecasts (from i = 2 to i = 25), are passed to the scheduling algorithm. The genetic algorithm decides now how to allocate the battery setpoints for i = 2, 3, …, 25, updating the values previously chosen if a better solution is found for the new available forecasts, and adding a provisional setpoint for the first hour of the following day. At this step, P_B^2 is set. This process is repeated hour to hour along the planning time horizon. For instance, if we want to schedule one day, the algorithm is executed and forecasts are updated a total of 24 times. At the initial time slot of each algorithm run, constraints (6) and (7) must be satisfied regarding SoC and the power setpoint established at the preceding execution. In this way, the h2h strategy is able to modify the setpoints which were decided by itself before, with the aim to fit better to new forecasted conditions with sufficient anticipation to make corrections if they are required. Moreover, it always keeps a scheduled time window of 24 hours that allows to consider the expected future needs, so that a reserve in advance nature is introduced spontaneously. Another good characteristic of this approach is that the probability of discrepancies between actual data and forecasted values used for computing the definitive setpoints P_B^i is reduced. It is because these forecasted values correspond to the first time slots of the predicted patterns, whose forecasts error range is lower (40% in the case of generation forecasting and 70% for electricity load forecasting, at most). Therefore, it is more improbable that a non-valid battery profile would be applied to real conditions.

C. Planning Quality Indicators and Energy Evaluation Indexes

In order to assess their performance, solutions provided by both management approaches must be compared to the theoretical charge/discharge profile obtained if forecasts were perfect, i.e., if forecasts and real conditions would completely match and no errors were made. This reference can be calculated running the charge/discharge decision making procedure of Section III.A over the whole-time horizon to manage, N, instead of the 24-hour horizon, based on actual recorded generation and demand profiles. However, to be coherent with the persistent 24-hour ahead time window of the h2h management, it is compulsory to simulate N + 24 hour to avoid distorted comparisons, although the asked solution only will be composed by the first N steps. Since it is an offline simulation about past data, carried out a posteriori, it has no sense to apply the hourly updating-reallocation approach in this scenario. It is assumed that the solution computed in this way is the best.

Due to their simplicity and easy comprehension, Mean Absolute Error (*MAE*) and Mean Absolute Percentage Error (*MAPE*) were chosen to measure the quality of the solution provided by each management method, in terms of fitting the offline best solution. These indicators are calculated as

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|A_i - F_i\right|, \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - F_i}{A_i}\right|, \tag{9}$$

where A_i and F_i represent actual and forecasted values at each hour i respectively.

Another interesting analysis consists in evaluating the impact of both approaches when their respective solution P_B is implemented in real conditions in terms of feasibility and energy exploitation. The selected evaluation indexes are presented next (note that they are calculated taking as common base the actual generation and demand profiles; variables P_G and P_D remark it adding the suffix "actual"):

- Self-consumption rate (*SC*), defined as the percentage of on-site generation directly consumed at the prosumer installation,

$$SC = \sum_{i=1}^{N}\min\left(P_{D,mod}^{i}, P_{G,actual}^{i}\right)\Big/\sum_{i=1}^{N}P_{G,actual}^{i}\,. \tag{10}$$

- Self-sufficiency rate (*SS*), defined as the percentage of local demand covered by the prosumer's energy sources,

$$SS = \sum_{i=1}^{N}\min\left(P_{D,mod}^{i}, P_{G,actual}^{i}\right)\Big/\sum_{i=1}^{N}P_{D,actual}^{i}\,. \tag{11}$$

- Imported energy (E_{imp}), defined as the sum of the hourly power grid flows from grid to prosumer system (negative sign),

$$E_{imp} = \sum_{i=1}^{N}\left(P_{grid}^{i}\cdot\Delta t\right)\ \forall\ P_{grid}^{i} < 0\,. \tag{12}$$

- Exported energy (E_{exp}), defined as the sum of the hourly power grid flows from prosumer system to distribution grid (positive sign),

$$E_{exp} = \sum_{i=1}^{N}\left(P_{grid}^{i}\cdot\Delta t\right)\ \forall\ P_{grid}^{i} > 0\,. \tag{13}$$

- Global grid energy (E_{grid}), defined as the energy exchange net balance between prosumer and grid,

$$E_{grid} = E_{imp} + E_{exp}\,. \tag{14}$$

These indexes are calculated with 1-hour resolution, according to the time step established for the scheduling problem. This may imply that *SC* and *SS* were slightly overestimated, but errors are generally very low [12]. Generation curtailment maneuvers are not considered, but they can be related to E_{exp}.

IV. Results and Discussion

The exposed scheduling problem and the two discussed management approaches were simulated in application to the case study proposed in Section II, considering SoC_{init}^{1} =10%. The planning time horizon comprises four days, i.e, N = 96 hours. Actual recorded data (Fig. 2(a), blue lines) include different generation patterns, in the sequence sunny – cloudy and intermittent – completely overcast – sunny with some

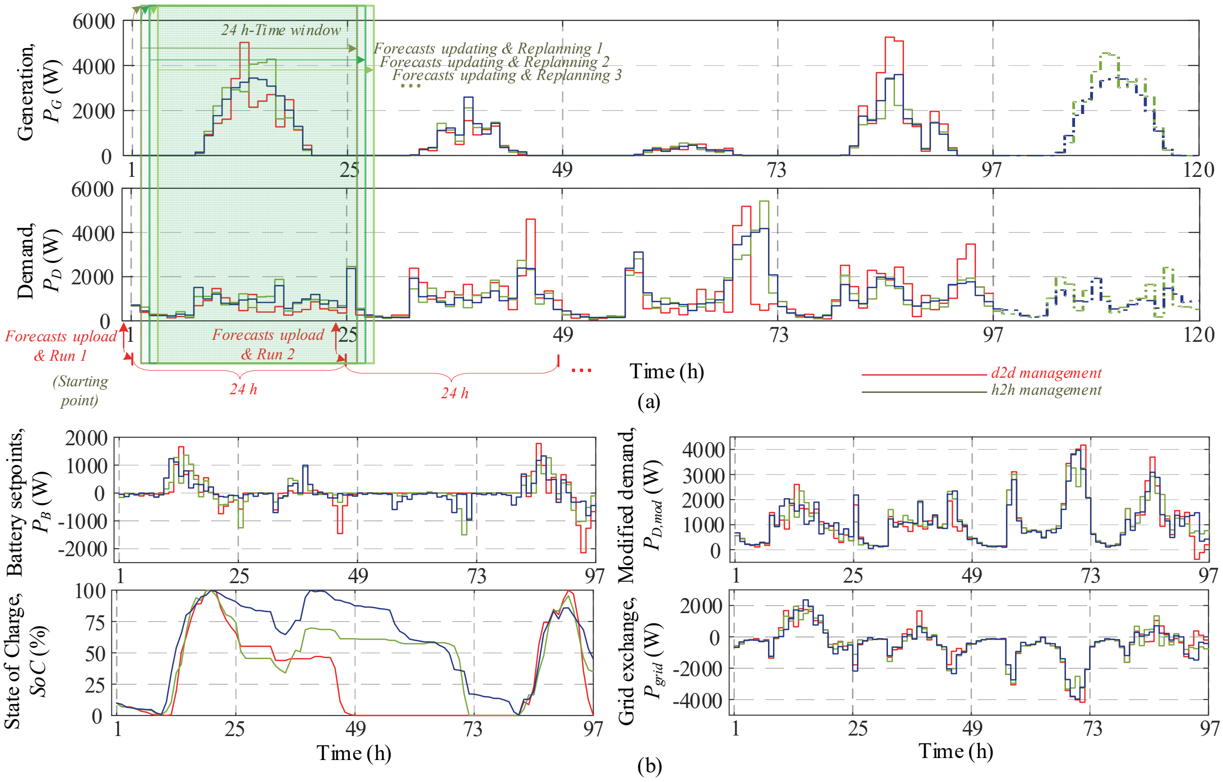

Fig. 2. (a) Generation (top) and demand (bottom) forecast profiles for the d2d approach (red) and the h2h approach (green), and related actual data (blue). The figure includes help to understand the methodology. (b) P_B, $P_{D,mod}$, SoC and P_{grid} profiles obtained by the d2d approach (red), the h2h approach (green) and the offline simulation (blue).

clouds. The third day presents the poorest production and the highest electricity consumption, so it is the most critical day. Note that a fifth day appears in Fig. 2(a) for the offline simulation (blue dotted lines) and the hourly updating-replanning method (green dotted lines). It represents the extra 24 hours required by them.

Fig. 2 also shows the forecasted generation and demand profiles based on a random vector applied to the real data. Their accuracy is notably improved when hourly updates are applied (*MAE* – calculated over a 96-hour time horizon – is 123.26 W for generation and 191.89 W for demand, in contrast to 194.44 W and 461.96 W respective *MAE* values when forecasts are made only every 24 hours). Note that the predicted values for the first hour of each day – corresponding to midnight – are the same for both methods, since the forecasting uploading coincides. In fact, the replanning starts one hour later than the d2d strategy, so it takes as starting point the first step computed by the d2d management first run (see Fig. 2(a)). For this reason, P_B^1 and its associated variables are the same for both methods, as Fig. 2(b) shows.

Simulation results prove that the algorithm enforces power and SoC constraints. They also demonstrate that the scheduling performance is improved when the h2h approach is applied, since it offers a more accurate tracking of the offline best solution than the d2d approach – *MAE* gets better from 243.96 W to 216.17 W regarding P_B , with a maximum P_B^i deviation reduction of 400 W approximately, whereas *MAPE* of $P_{D,mod}$ is 21.92% versus 24.59% with the "day to day" strategy (*MAPE* cannot be used to evaluate P_B because the best solution reference contains setpoints equal to 0, which would cause a singularity problem). This improvement is especially remarkable for the SoC management, achieving a lower *MAE* (14.92% instead of 31.27%). Observing Fig. 2(b), it can be seen that the replanning strategy SoC curve fits much better to the reference SoC pattern (the best) than the another one. Differences are noteworthy from the middle of the second day. The third simulated day presents a high energy deficit, but the d2d management does not know this circumstance, so it discharges the battery until it is depleted at the end of the second day because it is the best operation considering only the second day. However, the battery is completely empty at the beginning of the third day and cannot help to smooth the energy deficit, so this whole amount has to be supplied by the grid. The h2h management works in a different way, closer to the best solution in real conditions, since it anticipates the energy deficit at the third day and acts reserving stored energy to discharge it at the end of the third day, when the highest energy deficit is expected. Notice that when this discharge takes place, forecasts of the following day are available and expected generation is good; if a new negative balance was expected, the algorithm may make the decision of keeping a stored amount in reserve with the aim to be ready to face future needs. This characteristic leads to maintain at the end of the 4-day scheduling period a SoC value equal to 34.74%, according to the generation and demand forecasted for the following day – near the 45.07% computed by the offline simulation – whereas the d2d method finishes with the battery empty again. A result of this fact is that that the battery remains empty a

TABLE II. EVALUATION INDEXES

Evaluation index	d2d management	h2h management	Offline best solution
SC (%)	71.05	73.22	75.59
SS (%)	42.81	44.11	45.54
E_{grid} (Wh)	-39618	-41494	-42052
E_{imp} (Wh)	-57239	-57792	-56910
E_{exp} (Wh)	17621	16298	14858

[a] Negative values mean that grid supplies energy to prosumer.

shorter time with the h2h management, which aids to prevent degradation. Moreover, this reluctant character to full discharges promotes another advantage regarding battery lifetime preservation: a global operation around an intermediate SoC value of 45.90%, recommended for battery aging reduction [13], unlike the much lower mean SoC of the d2d strategy, equal to 29.30%. This idea is reinforced by the mean SoC obtained by the offline simulation for the best global operation, established in 59.12%.

Fig. 2(b) profiles present two interesting aspects. One of them is visible at the end of the fourth day. In this period, $P_{D,mod}$ becomes negative for the d2d strategy, which implies that battery is injecting energy straightly to the distribution grid, despite the problem constraints forbid it. This anomaly is not a failure of the decision making procedure, but it is a consequence of the high demand forecast error made for those hours (see Fig. 2(a)), which is justifiable considering that the forecast were carried out more than 20 hours ahead without updates. Thus, the expected demand is much higher than the actual one (around 1700 W for $i = 94$), in a way that the planned battery setpoints are excessive to cover only the electricity consumed actually and the surplus is exported to the grid. This fault is penalized by *SC* and *SS* indexes. In this sense, the h2h strategy seems more robust. The second interesting aspect is noticeable in P_{grid} profiles, but now in relation to the h2h approach. Generally, P_{grid} presents a smoother curve for the h2h management than for the d2d one, which is advantageous from the grid operator viewpoint. However, in the range of $i = 70$, the h2h strategy fits worse to an abrupt negative peak in the P_{grid} profile shown by the offline solution than the d2d one. This fault could be explained considering that updated forecasts may include some particular values less accurate than the obtained with previous forecast – since they are based on a random vector – and, thus, it gets worse the solution at certain steps.

Table II summarizes the resulting energy evaluation indexes. The h2h strategy slightly improves *SC* and *SS*. Indexes regarding energy exchanges with the grid are also more similar to the respective values of the offline simulation, with the exception of E_{imp}, but it is due to the less sharp shape of P_{grid} at $i = 70$ above mentioned. E_{grid} index presents higher absolute values for the h2h management and the offline solution as a consequence of keeping a certain SoC level as a reserve. Finally, discrepancies in evaluation indexes between the d2d and h2h methods are low because resulting errors with different sign are counteracted with their aggregation over the whole scheduled period.

V. CONCLUSIONS

In this work, a battery energy management strategy based on forecasting to schedule it in advance was presented in a general scenario non-affected by specific regulatory frameworks and, thus, applicable in most cases. Forecasts inaccuracy – especially high for irregular individual household demand patterns – exhibits a heavy impact on provided solutions, so an improved approach is proposed to address this problem.

The improved method, based on hourly forecasts updating and replanning, offers more quality results and the chance to anticipate future energy needs. Thus, a better SoC management is achieved, with good properties regarding battery lifetime preservation. Moreover, self-consumption and self-sufficiency are enhanced with only forecasts updates and setpoints reallocation, without adding sophisticated strategies.

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