Real-time optimization of the battery banks lifetime in Hybrid Residential Electrical Systems

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***Abstract*—We present a real-time optimization framework to manage Hybrid Residential Electrical Systems (HRES) with multiple Energy sources and heterogeneous storage units. HRES represents urban buildings where photovoltaic (PV) or other renewable sources are installed along with the traditional connection to the main grid. In this paper heterogeneous storage units are used to realize energy buffers for the exceeding energy produced by the renewable when buildings and the grid are not available to accept it. We considered two different battery banks as electric energy storage, in particular lead-acid as the primary one for its low price and low self-discharge rate; while the lithium-ion chemistry is used as secondary bank because of the higher energy density and higher number of cycles. The proposed optimization strategy aims at maximizing the lifetime of the battery banks and to reduce the energy bill by managing the variability of the PV source, in price-varying scenarios. We used a Dynamic-Programming (DP) algorithm to schedule off-line the use of the lead-acid bank minimizing the number of cycles and the Depth-of-Discharge (DoD) under given irradiance forecasts and user load profiles. Forecasts of the user loads and of the renewable energy intake are introduced in the optimization. Moreover a Real-Time scheme is introduced to manage the lithium bank and to minimize the need and the purchase of energy from the Grid when the actual demand does not fit the forecast. Our simulation results outperform the state of the art where the efficiency of both banks is not taken into consideration, even if complex approaches based on DP are used.**

I. Introduction and Related Work

The demand of electric energy increases every day. Traditional fossil fuel sources are no more sufficient to satisfy the energy demand. Concerns about carbon emissions and global warming imposes the need of more sustainable sources and a change in people's lifestyle.

Recently, *Demand Side Management* policies have been gathered the attention of the scientific community, to make users aware about wasted energy and to give them an active role in the energy supply chain. Another important innovation is the massive diffusion of renewable power generation sites, even if scattered in an unregular fashion and usually at the periphery of the electricity grid. Moreover, decreasing cost of installation, is permitting many end-users to build their own power supply system directly at home. This has practically transformed buildings into energy agents of the supply chain and end-users have gained an active role to influence the control strategy for the grid.

The model of urban buildings is, therefore, becoming bidirectional where hybrid and multiple sources of energy can be converted into electrical energy and injected into the mains. Moreover energy can be stored locally by end-users in their premises. The heterogeneity of such systems both for the generation and the local storage, justifies the name of Hybrid Residential Electrical Systems (HRES). Solar energy is the most effective source employed in HRES since the PV module is located near the users and the harvested energy can be immediately available without distribution. Moreover, it is quite easy to predict the future energy intake in the short-term [1] with very accurate energy forecasting algorithms. Notwithstanding the advantages, the introduction of renewables at the periphery of the Grid has radically changed the topology and the management of the electricity supply grid with new challenges to address.

Renewable energy sources are not constant over the time, their intensity depends on weather, geographical position of the plant and seasons, moreover a maximum in the energy intake never corresponds with a maximum in the demand. To this purpose, efficient algorithms designed to forecast efficiently the residential load consumption, are still far to be designed for well known constraints already described in literature [2]. Furthermore, to tackle the imbalance between energy intake and demand, a widespread monitoring system of the produced and consumed power and energy over the time, such as the one proposed in [3] is necessary.

From the point of view of the management, many solutions have been proposed in literature. When the renewables outweigh the demand in the grid, the usage of electrical energy storage systems to *park* temporarily the exceeding energy is the most effective method which permits also to manage automatically the HRES [4]. Furthermore, hybrid systems exploiting different battery technologies can combine different advantages, as proposed in [5].

All the approaches presented in the literature are characterized by a dual goal: on one side, to reduce the user's electricity bill [6], on the other to reduce and to balance the total load of the future Smart Grid. Finally HRES can be used to elaborate complex scheduling algorithms for appliances to achieve peak shaving and load balancing [7], [8].

In this field the many efforts have been also oriented to the optimization of several parameters such as price, battery lifetime, peak shaving; or to the models used to represent and simulate the environment. To the best of our knowledge not enough effort have been dedicated to adaptively update the real-time scheduling and to manage

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efficiently the charge and discharge of the battery banks in hierarchical fashion safeguarding their lifetime.

Considering that the cost of a battery bank is about 20k€, it takes a large part of the total cost of the whole HRES. Even if the expected lifetime is of 15 years, the long term usage degrades the capacity of the battery. If the charging-discharging cycles are correct, batteries are expected to retain up to 85% of their initial capacity after five years of use; while if not properly used, the capacity retain decreases with a rate of about 20% every 2 years. These figures justify an accurate management of the battery banks, which is fundamental to reduce maintenance and to minimize the final costs.

The contribution of this paper is to define an approach to minimize the electricity bill of a HRES, taking into account the cost policies of the energy from the main, in the HRES scenario by exploiting forecasts both of the user loads and of the energy intake from renewables. The proposed system uses two battery banks with different priorities and roles. The dynamic programming framework computes off-line the optimal scheduling policy for a primary battery based on the renewables and load forecasts for a determined horizon. Our main contribution is the introduction of the real-time optimization scheme which manages a secondary battery to compensate for the difference between expected and actually available green-energy and user-demand. The optimization constraint added to price minimization is the maximization of the lifetime of the battery banks. We considered technological limits, the optimal DoD and charge/discharge cycles with different priorities to achieve the minimum number of cycles possible.

The paper is organized as follows, Sec. II presents a detailed description of the HRES envisioned and relative models used in the simulations. Sec. III describes the implemented policies which will be then evaluated in Sec. IV. Sec. V concludes the work.

II. Hybrid Residential Electrical System

The Hybrid Residential Electrical System models a heterogenous urban building, connected to the main Grid, where PV modules and energy storage system are installed. Renewable energy and batteries should completely sustain the load of the inhabitants or, at least, provide enough free energy during periods with the highest energy price. We defined two constraints to the simulated system: the exceeding energy can not be injected into the main Grid (if it can be stored) and a price varying scenario for the energy taken from the grid. The system architecture, depicted in Fig. 1 uses two battery banks of different technology (lead-acid as primary and lithium-ion as secondary) and dimensions as energy storage units, the aforementioned PV module and the bidirectional Charge Transfer Interconnect bus (CTI-bus) managed by a dedicated module, as presented in [6]. Each storage unit is connected to the CTI by means of a bidirectional DCDC converter for level shifting and charge routing, while the PV's one is unidirectional. The CTI itself is connected to the building's supply grid by means of unidirectional AC-DC. The PV module embed a MPPT controller to maximize the energy scavenged. The

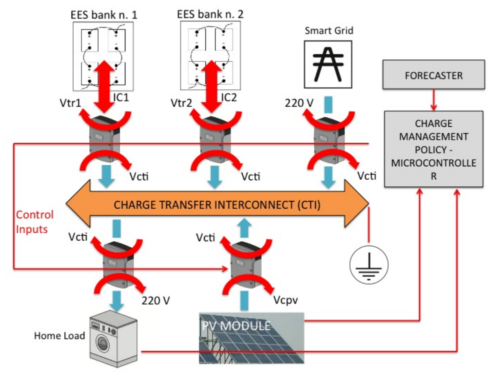

Fig. 1. Hybrid Residential Electrical System with its control parameters.

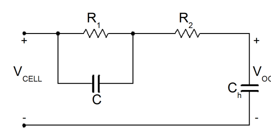

Fig. 2. Battery equivalent electric circuit.

CTI controller manages the voltages on the CTI-bus and on the bidirectional converters. It computes the optimal control strategy to use with the lead-acid array by using irradiance and load forecasts while the lithium-ion one is used to compensate the error in the forecast in real-time. Since the energy scavenged by the PV module can not be re-injected into the main, the optimization problem results in the computation of the optimal charge/discharge sequence of the energy buffers.

We developed a discrete-time simulating framework in Matlab environment to model and evaluate the proposed HRES manager. In this section we present the model used to describe and manage the Energy Storage System (ESS) made of two heterogeneous storage arrays, the PV scavenger and their interfaces with the CTI (DC-DC and AC-DC).

A. Energy Storage System Models

Hybrid ESS combines the advantages of the two different battery technologies and, contemporary, mitigates their drawbacks. Lead-acid technology offers better performance in a wider temperature range, have lower price with respect to other technologies and are easier to recycle. Lithium-ion instead performs better in terms of energy density, total number of cycles, charge time and self discharge rate. Considering these features and their role in the system, we decided to model the lithium-ion bank with half the capacity of the lead-acid one. We model both battery banks with the equivalent electrical circuit [9], [10]. The advantage of the equivalent model resides in its simplicity which translate in low computational complexity with respect to more complex models (for example electrochemical, analytic or stochastic). Fig. 2 depicts the adopted model where V_{CELL} is the cell Voltage, V_{OC} is the open-circuit Voltage, C_h is the effective capacity while other parameters model the parasitic effects, R_1 and R_2 are the total internal resistance and C is the parasitic capacitance due to charge deposition on the electrodes. The relevant parameters to evaluate the

TABLE I. Lead-acid Battery Parameters

Battery Model	HUP SO-6-85-21/12
Voltage	12 V
Ah rated 20Ah	1055
Ah usable 20Ah	844
Wh rated 20Ah	12660
Wh usable 20Ah	10128
Min charge Current	85 A
Max charge Current	170 A

TABLE II. Lithium-ion Battery Parameters.

Battery Model	CP 12 V Li-ion
Voltage	12 V
Ah rated 20Ah	400
Wh rated 20Ah	5280
Charge Operation Voltage	60 V
Discharge operation Voltage	36.8 V
Standard Current	50 A

state of each bank in the ESS are the State of Charge (SoC), the open-circuit Voltage (V_{oc}) and information about aging in terms of State of Health (SoH) and State of Life (SoL). The model takes in input the control current (IC_{bank}) to compute the state at the end of each computation time-slot. A more detailed description of the equivalent electrical circuit model can be found in [7].

We evaluated the total capacity of the ESS considering the average power required daily during winter equal to 6000 $[Wh]$ and assuming to have enough autonomy to sustain the HRES for four days without sun. By means of Eq. 1 we get a total capacity of 2220 $[Ah]$:

$$C_{tot} = \left(\left(P_d^{avg} \cdot n_{days}\right) / DoD_{max}\right) \cdot K / V_{sys} \qquad (1)$$

where P_d^{avg} is the average daily power, n_{days} is the number of autonomous days, DoD_{max} the maximum Depth of Discharge equal to 25 %, V_{sys} the system Voltage and K the environmental temperature coefficient [11] equal to 1.11 for 60 $°F$. To summarize, the system we simulate consists of a primary lead-acid bank made of a series of four HUP Solar One SO-6-85-21/12, 12 V batteries (details are reported in Tab. I) and a secondary matrix of 4x4 Clayton Power, 12 V batteries (details are reported in Tab. II) for a total of 48 V.

B. Voltage Converters

The model of the bidirectional DC-DC and unidirectional AC-DC converters have been developed using their efficiency curve as suggested in [7]. This model correlates the efficiency of the converter with the normalized input power by means of a lookup table obtained by interpolation of experimental results. The resulting model is expressed by the Eq. 2.

$$\eta = 1 - (1/P_{in}) \cdot \left(0.0094 + 0.0043 \cdot P_{in} + 0.04 \cdot P_{in}^2\right) \qquad (2)$$

C. PV Model

The PV module has been modeled as a linearly varying power source. The output power depends on the irrandiance intensity and the environmental temperature [12], [13]. We considered a module made of 72 cells, all at the same temperature for simplicity. The PV module embeds a Maximum Power Point Tracking (MPPT) system to scavenge

TABLE III. Bidirectional Converter Parameters.

Converter Model	Sunny Island 6.0H
Rated Line Input Volt - Range	230 V - 172.5 to 264.5
Rated Power - Max AC Input Power	4600 W - 11500 W
Rated Current - Max Current	20 A - 120 A
Rated Frequency - Range	50 Hz - 40 to 70
Max AC Input Current	50 A
Battery-side Rated Input Voltage - Range	48 V - 41 to 63
Max Eff. - Self-Consump. Range	95 - 4 to 26 W

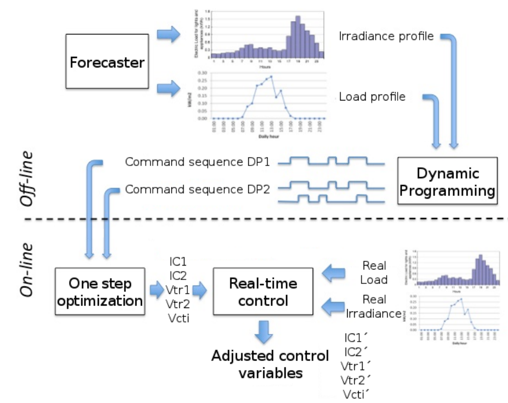

Fig. 3. HRES simulating framework.

the maximum possible power that has been evaluated using Eq. 3.

$$P_{PV} = \left[P_{PV,STC} \cdot (G_T/1000) \cdot \left(1 - \gamma \cdot (T_j - 25)\right)\right] \cdot N_{PV,S} \cdot N_{PV,P} \qquad (3)$$

The parameters were evaluated in Nominal Operating Cell Temperature (NOCT) and Standard Test Conditions (STC) which are the nominal output power $P_{PV,STC} = 165$ W in this case, the cell temperature T_j, irradiance level $G_T = 1000$ $W/m^2 @ 25°C$ and the temperature coefficient $\gamma = 0.043\%/°C$, while $N_{PV,S}$ and $N_{PV,P}$ are the number of series and parallel cells in the module. The cell temperature instead is then obtained using Eq. 4.

$$T_j = T_{amb} + (G_T/800) \cdot NOCT - 20 \qquad (4)$$

where T_{amb} is the environmental temperature, $G_T = 800$ W/m^2 @ $T_{amb} = 20°C$ and $NOCT = 45.5°C$.

III. Management Schemes

We evaluated a discrete-time, two-phase HRES management algorithm (DP1) that firstly computes (off-line scheduling) a long-term plan to use the battery banks which is then adapted to the real situation (real-time management). The preliminary scheduling scheme, based on the DP, manages the lead-acid bank. The real-time controller is an ad-hoc algorithm that compensate the deviation from the forecast by means of the lithium-ion battery bank. The proposed framework implemented in a simulator is depicted in Fig. 3. In our scenario we used hourly time-slots to discretize the simulation. During the off-line stage, the simulator computes user load and solar irradiance forecasts to be used as input of the DP. This module then evaluates the optimal charge/discharge profiles for the lead-acid battery bank or both, depending on the simulation goals as will be explained later on. The on-line stage optimizes the system control variables by evaluating the difference between forecasted and real power/irradiance profiles. In the same stage the controls variables (ref. Fig. 1) were optimized following the charge allocation scheme presented in [14]. In addition to the two forecasts, the simulator takes as input the horizon of the simulation, the daily price profile for the intake electric energy from the grid and the real data about irrandiance and load. In conclusion, we compute the electricity bill amount, the SoH and other battery related parameters to evaluate the performance.

For the sake of completeness we developed two other control strategies to compare the results of our implementation with other works in this field. Those are an hysteresis based controller (HST) and a state of art DP-based scheduler which use both battery banks with equal priorities (DP2).

A. Off-line scheduler

The DP-based off-line optimal scheduling scheme is a customizable algorithm which permits to adjust simulation parameters such as the number of battery banks. The reason is to use a single module to evaluate two configuration: the proposed approach (DP1) which uses one bank and a state of the art solution (DP2) inspired by [5].

The DP is a strategy to solve complex problems by splitting them into lower complexity ones. In the HRES scenario the goal is to define the sequence of transitions the lead-acid battery bank must follow to minimize the cost of the intake energy from the Grid. To this reason the battery bank can be fully charged (interrupted charges are not allowed to preserve battery's healt) when there is enough green energy and/or buying energy from the Grid in low-price periods. Each possible state and transition between them must be modeled and weighted, to compute the optimal path. To implement this scheme we started from the one proposed in [7]. With respect to the reference we model the battery state considering the SoC and the command charge/discharge (ON/OFF). In this case we doubled the number of possible combination but we can differentiate between the four possible transitions (from ON to OFF, ON to ON and so on) and define different weights for each of them.

As previously stated we implemented this algorithm also to optimize both battery banks during the off-line scheduling, to compare with the solution proposed in [5]. In this case we defined a different priority to solve the concurrent charging of both banks, in particular we chose to give higher priority to the primary since the lithium-ion can better sustain discontinuous charge cycles.

B. Real-time manager

The on-line scheduler represents the main contribution of this work. It has been implemented to solve two main issues in currently proposed solutions that come from the optimal management of lead-acid batteries; producers suggest to perform complete charge/discharge cycles to maximize its SoH: i) in case of excess of green-energy with respect to the user needs, this would be wasted if the primary was discharging; ii) in case the primary bank was charging and the user load was exceeding the forecast it would be preferable to have another buffer to avoid the use of the grid. The on-line algorithm manages these situations by scheduling the lithium-ion bank activity. In normal operating conditions, for example when forecasts and real load are equal, the DP-optimized scheduling is used for both the arrays. Once again we decided to use different priorities between the banks to favor the use of the primary one by imposing higher charge/discharge currents.

C. Hysteresis

This is the simplest scheduling algorithm to use with battery banks, the input power coming from the PV module is used as primary source and it is used mainly to supply the user load and then to charge the ESS in case of excess. Given its simplicity this scheme works online by updating the ESS state every time-slot. The intake from the supply Grid is used only in case the SoC of both the battery banks are below a fixed threshold (SoC_{LW}^{TH} 70% for lead-acid and 75% for lithium-ion). Generally, it requires the definition of two thresholds on the SoC ($SoC_{LW}^{TH} < SoC_{HG}^{TH}$) that are used to change the state of the battery bank. If the SoC is below the lower threshold the bank starts recharging until it reaches the higher one ($SoC_{HG}^{TH} = 100\%$) when they can be discharged again. In a price-varying scenario we modified this technique by introducing another intermediate threshold ($SoC_{LW} < SoC_{MD} < SoC_{HG}$) to take actions in case of higher energy price. In this way, if the SoC is above SoC_{MD} and the battery is recharging using energy purchased form the Grid, the process is suspended.

IV. RESULTS

In this section we presents the results obtained comparing the proposed HRES management algorithm and the other two presented above. In the following DP1 represents the proposed approach, DP2 the state of art scheme and HST the hysteresis technique. Four climatic scenarios were evaluated for comparison:

- ws-a Regular and intense irradiance (more than 80% sunny days, Summer irradiance);
- ws-b Regular irradiance (more than 80% sunny days, Spring irradiance);
- ws-c Irregular and intense irradiance (no more than 30% sunny days, Fall irradiance);
- ws-d Regular but weak irradiance (more than 80% sunny days, Winter irradiance).

Each climatic scenarios were corrupted by two different kind of errors, the forecasts were computed by applying the following modifications to the real data-sets:

- E0 The amplitude was randomly modified (1/3 max) and shifted in time (2 hours max);
- E1 Previous corruption and two cloudy days (no irradiance) forecasted as sunny.

An example of the above irradiance profiles is depicted in Fig. 4, while Fig. 5 represents an example user load. The pricing policy considered in our simulation, is a time-based rate, which is commonly applied in many countries

TABLE IV. RESULTS COMPARISON IN FIRST WEATHER SCENARIO (WS-A).

WS-A	DP1-E0	DP1-E1	DP2-E0	DP2-E1	HST
One Week					
C [€]	0.16	0.4	1.7	1.9	0.73
CC1 [#]	5	7	8	8	8
CC2 [#]	11	13	14	13	10
DoD1 [%]	90	92	98	98	98
DoD2 [%]	88	86	95	94	88
var1	1	1	0.16	0.6	0.16
var2	11	15	0.87	1.6	9
Two Weeks					
C [€]	1.24	2.39	3.41	3.9	1.41
CC1 [#]	13	17	17	16	16
CC2 [#]	33	31	28	24	20
DoD1 [%]	83	82	97	96	96
DoD2 [%]	87	84	92	90	87
var1	1.0	1.3	1.5	3.7	2.94
var2	1.2	1.3	5.4	7.4	8.69

TABLE V. RESULTS COMPARISON IN FIRST WEATHER SCENARIO (WS-B).

WS-B	DP1-E0	DP1-E1	DP2-E0	DP2-E1	HST
One Week					
C [€]	0.4	0.8	3.1	3.2	1.14
CC1 [#]	5	5	9	9	8
CC2 [#]	8	9	13	12	11
DoD1 [%]	86	81	96	95	95
DoD2 [%]	79	73	91	92	81
var1	3.8	4	1.3	2.2	2.2
var2	12	14	5.7	2.4	5.2
Two Weeks					
C [€]	1.79	3.24	5.79	6.7	1.68
CC1 [#]	14	10	18	19	16
CC2 [#]	21	22	27	23	20
DoD1 [%]	78	70	95	93	93
DoD2 [%]	75	75	91	89	83
var1	11	3.7	1.2	3.1	3.4
var2	10	11	2.2	4.7	4.5

TABLE VI. RESULTS COMPARISON IN FIRST WEATHER SCENARIO (WS-C).

WS-C	DP1-E0	DP1-E1	DP2-E0	DP2-E1	HST
One Week					
C [€]	2.6	3.8	8.7	9.9	6.5
CC1 [#]	20	20	22	19	16
CC2 [#]	28	27	33	28	24
DoD1 [%]	81	78	95	92	91
DoD2 [%]	81	76	88	83	85
var1	11	12	2	2.9	7
var2	16	12	7.6	7.7	11
Two Weeks					
C [€]	2.6	3.78	8.7	9.9	6.5
CC1 [#]	20	20	22	19	16
CC2 [#]	28	27	33	28	24
DoD1 [%]	81	78	95	92	91
DoD2 [%]	81	76	88	83	85
var1	11	12	2	2.9	7
var2	16	12	7.6	7.7	11

TABLE VII. RESULTS COMPARISON IN FIRST WEATHER SCENARIO (WS-D).

WS-D	DP1-E0	DP1-E1	DP2-E0	DP2-E1	HST
One Week					
C [€]	3.8	4.5	12	12.5	7.2
CC1 [#]	15	15	26	25	8
CC2 [#]	26	24	36	34	11
DoD1 [%]	77	76	95	94	84
DoD2 [%]	71	71	88	87	79
var1	7.9	9	1	1.5	5
var2	3	3.3	5.9	5.2	3.6
Two Weeks					
C [€]	3.85	4.5	12	12.5	7.2
CC1 [#]	15	15	26	25	15
CC2 [#]	26	24	36	34	25
DoD1 [%]	77	76	95	94	84
DoD2 [%]	71	71	88	87	79
var1	7.9	9	1	1.5	5
var2	3	3.3	5.9	5.2	3.6

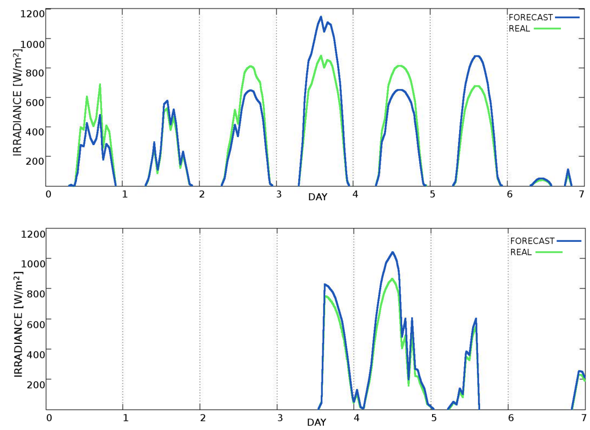

Fig. 4. Irradiance profile example for 1 week, W/m^2 versus weekdays. The blue line represents the real data while the green the forecast corrupted with method E0. WS-A (top) and WS-D (bottom) scenarios.

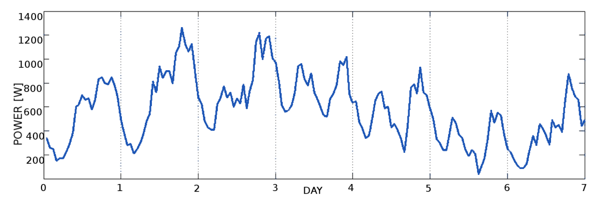

Fig. 5. End user load profile example for 1 week, W versus weekdays.

of the EU (with some variations). It consists of two rates: the high-rate is applied during the time interval $6h-20h$ of the working days in the week, otherwise a low-rate is considered in the bill. Fig. 6 presents the results of the DP1 manager in case of WS-B weather scenario and E0 forecast corruption. Notice that the optimal control law computed off-line (top graph, green curve) is not completely used in the final result (bottom graph, blue curve). In fact, the secondary energy buffer is recharging as soon as exceeding power is available (highest number of peaks in the green curve of the bottom graph). Another interesting result of our hierarchical implementation can be evaluated by observing the middle of the fifth simulated day (Fig. 6 top). The lead-acid battery has not been scheduled to recharge for hours since the user demand (red curve) is increasing very fast and the power from the renewables is decreasing. This force the scheduler to purchase energy from the grid (charge commands, the blue peaks) during the highest price slot (cyan curve). If we then consider the output of our controller after the real-time optimization (Fig. 6 bottom) we can notice that during the fifth day the primary battery is almost fully charged while the secondary has been used to compensate the lack of renewable energy.

We used the following parameters to compare the performance, summarized in Tab. IV to VII:

C	Total cost of the energy in €;
CC1,CC2	Number of cycles of lead-acid and Lithium batteries respectively;
DoD1,DoD2	Mean DoD of the two banks in %;
var1,var2	DoD Variance.

The number of cycles states how many times a charge cycle started, obviously the smaller the better. The Mean

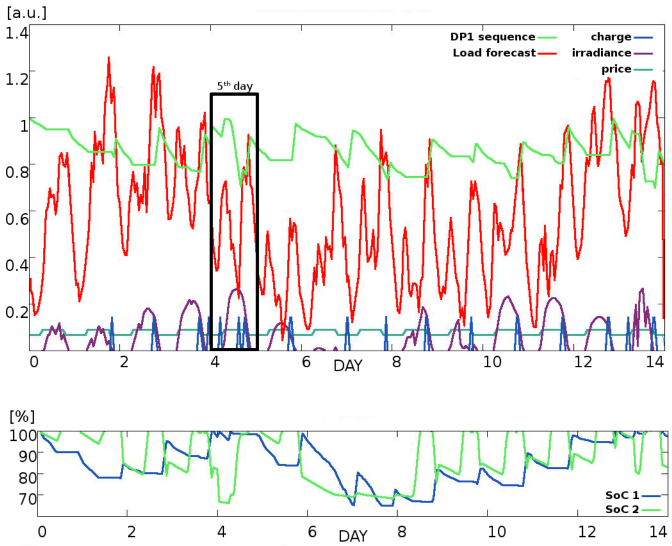

Fig. 6. Example results for WP-B E0 simulation with horizon 14 days. Output of the DP1 off-line algorithm (top) and real-time updated SoC for both banks (bottom). In the top graph, the vertical scale is normalized and refers to the optimal path (green curve) for the SoC measured in %. The other quantities have been scaled and adapted to obtain a qualitative feedback of the off-line scheme. In the bottom one the actual SoC output of the real-time simulator is referred in % with respect to simulated days.

DoD is the mean of all the minimum DoD reached in the simulation and considered also its variance we can evaluate the pattern of use of a single array. Lead-acid batteries prefer complete charge/discharge cycles, big DoD, high variance and reduced number of cycles. Lithium-ion instead work better with small DoD and reduced variance, while the number of cycles is not relevant. In scenarios WP-A and WP-B (Tab. IV and Tab. V) the DP1 scheme clearly outperforms the other two methods in terms of money saving and reduced number of cycles for the primary ESS. In the WP-C scenario (Tab. VI) instead we can observe that the HST management scheme offers the best battery usage. In the last simulated scenario (WP-D Tab. VII) DP1 and HST offer comparable performance in terms of number of cycles, even if the savings are always higher with the proposed scheme. In general we can state that in case of favorable weather conditions DP1 and HST have comparable results in terms of energy savings but the former one have the best performance in terms of primary battery lifetime. In case of adverse weather conditions DP1 is the best choice in terms of savings but the HST offers the best primary battery utilization pattern.

V. Conclusion

In this works we presented a management scheme to use in Hybrid Residential Electrical Systems (HRES) where PV module supply energy to the urban building and a hierarchical electrical Energy Storage System (ESS) is used to store exceeding green energy. The purpose of the ESS is to compensate the use of energy from the Main Grid. This goal has multiple benefits, from the user point of view it is possible to reduce the electricity bill; from the Grid side instead it permits to reduce the total load and to balance peak demands. The proposed scheme uses a ESS made of two different battery technologies, lead-acid and lithium-ion, to emphasize their combined performance and mitigate their limits. The two battery banks are used in hierarchical fashion, the lead-acid one serves as primary buffer and its used is programmed in advance by means of a DP-based scheduling algorithm. The other energy buffer is managed in real-time by a secondary scheduling algorithm to compensate for the difference between irradiance and user load forecast used by the DP-based off-line optimization. Our main contribution is the definition of a hierarchical framework for the HRES and the implementation of the real-time scheduler. We evaluated the performance in a wide range of weather conditions and for multiple time horizons. The proposed strategy achieves both money savings and a better long term state of health of the primary battery, compared with other scheduling algorithms.

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