Optimal management of energy storage systems for residential customers with photovoltaic generation

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***Abstract*—The growing focus that some big companies are putting on the electrical storage market is leading to a decrease in the cost of these devices, which are now becoming appealing also for residential applications, often coupled with the installation of photovoltaic panels. This poses the problem of the optimal management of energy storage systems for residential customers in order to fully exploit the benefits of both photovoltaic generation and storage. The solution to this problem is an integral part of home energy management systems, which are expected to play a key role in the smart grid of the future. The purpose of this paper is to propose and analyze different energy storage system management policies in a framework with real time pricing for both energy purchase and sell. This pricing scheme is already present in some markets worldwide and will likely become more and more common in the next years.**

***Index Terms*—Energy storage systems, home energy management systems, mixed-integer programming, receding horizon.**

I. Introduction

The growing interest towards Energy Storage Systems (ESSs) is motivated by the multiple services that these devices are able to provide. Currently, most common applications of ESSs are peak management, ancillary services and integration of distributed generation [1]. Peak management consists in storing energy in the ESSs when electricity is cheaper for later use during peak times, when electricity is more expensive, in order to balance demand and supply. When used for ancillary services, ESSs can help deal with frequency and voltage issues possibly arising when the unbalanced power supply and demand cause partial power failures, and even black-outs. Moreover, ESSs can be used to mitigate the fluctuation of power generation from renewable sources, thus facilitating their integration in the power grid.

ESSs installed at the consumers' premises can provide significant benefits to both the end customers and the network operator. Thanks to recent technological advances, residential ESSs are becoming more and more appealing because of the sharp decrease of their cost. A further incentive to the adoption of residential ESSs is the growing diffusion of Real-Time Pricing (RTP) schemes for energy billing. This pricing scheme is already present in some countries [2], and is especially useful to implement demand-side management policies, encouraging the reduction of energy consumption during peak times. In this context, residential ESSs allow consumers to further reduce the electricity bill by suitable charging and discharging policies, yielding significant cost savings, especially when there are large price fluctuations.

The most interesting scenario is when ESS and photovoltaic (PV) and/or micro-eolic generators are jointly used [3], [4], [5]. The main advantage concerns a smarter peak management by exploiting the energy generated from renewable sources, and stored in the ESS. Moreover, it is possible to sell energy to the network not only when there is generation, but also when energy remuneration is higher.

The optimal ESS control is an integral part of home energy management systems (HEMSs), which are responsible for monitoring and managing the operation of a number of devices and smart appliances. The main purpose of HEMSs is to avoid load peaks and reduce the electricity bill, while guaranteeing certain levels of comfort required by the customer, exploiting the flexibility of the most innovative home appliances [6], [7]. An aspect which makes the ESS control more challenging is the uncertainty affecting demand and generation. In particular, distributed generation is heavily dependent on weather conditions and, consequently, characterized by high uncertainty. On the other hand, in a HEMS framework demand is typically less uncertain, being the result of optimal scheduling of the appliances.

In this paper, we propose the formulation of the optimal ESS control problem, minimizing the energy cost over a given time horizon for a consumer equipped with PV panels. In order to cope with uncertainty on PV generation, an implementation based on a receding horizon scheme is adopted. At each time step, the optimal ESS control problem is solved over a prediction horizon of fixed length. Then, only the first control inputs are implemented. The same procedure is repeated at the next time step with updated PV generation forecasts. The receding horizon control strategy is compared with a greedy policy not requiring these forecasts to be available. The comparison is carried out using real data from an Italian LV network and the Italian spot market. Moreover, a sensitivity analysis is performed with respect to some key parameters of the receding horizon implementation.

The paper is structured as follows. Section II presents the formulation of the optimal ESS control problem, whose receding horizon implementation is described in Section III. Section IV reports the numerical results, while conclusions are drawn in Section V.

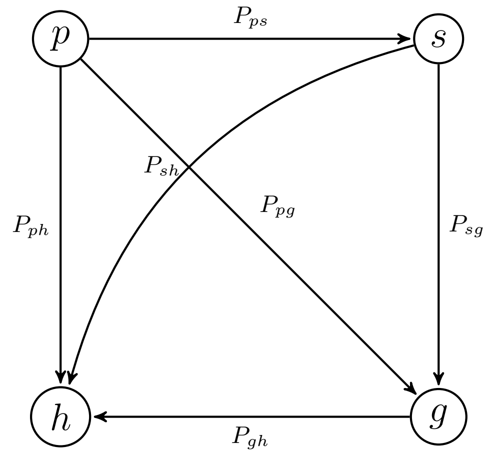

Fig. 1. Graph of the power flows between the components of the home energy system and the grid.

II. Problem Formulation

The considered scenario consists of a residential customer equipped with PV generation and ESS. Figure 1 shows the admissible power flows in our setup between the home appliances (h), the PV panel (p), the ESS (s) and the power grid (g). Variables $P_{ij}(t) \geq 0$ represent the active power flowing from i to j, averaged over a sampling time ΔT, where t is a discrete time index.

The ESS is assumed to have a uni-directional connection with the grid, i.e. the storage cannot be charged from the power grid. This assumption is motivated by technological reasons, since many residential systems include PV panels, storage and inverters in an integrated solution which does not allow ESS charging from the grid. Moreover, the same assumption rules out arbitrage. In this paper, this makes it possible to understand the actual benefits of residential ESSs for both customers and network operators. Indeed, the distributed generation maintains its "fair" behavior, allowing for customer's energy independence, while providing support to the network operator during peak times. Nevertheless, if needed, bi-directional power flow between ESS and the grid can be introduced with minor modifications to the proposed model.

The objective of the ESS control policy is to minimize the total energy cost over a given time horizon of length T. This problem can be cast as

$$\min \sum_{t=1}^{T} \left[r(t)\, P_{gh}(t) - v(t)\, \left(P_{sg}(t) + P_{pg}(t)\right)\right] \Delta T, \quad (1)$$

where $r(t)$ is the purchase price and $v(t)$ is the selling price, both assumed to be real time prices [3]. In (1) the decision variables are all the power flows $P_{ij}(t)$ shown in Figure 1. These must satisfy a number of technical constraints. The generated PV power $P_f(t)$ is distributed among the home appliances, the grid and the ESS, i.e.

$$P_f(t) = P_{ph}(t) + P_{pg}(t) + P_{ps}(t). \quad (2)$$

The energy demand $D(t)$ of the appliances must be satisfied by the power supplied by the PV panel, the ESS and the grid, i.e.

$$D(t) = P_{ph}(t) + P_{sh}(t) + P_{gh}(t). \quad (3)$$

The ESS is subject to charging and discharging ramping constraints, denoted by $\overline{P_c}$ and $\overline{P_d}$, respectively. Moreover, the ESS cannot be charged and discharged at the same time. Introducing a binary variable $y_s(t)$, which is equal to 1 if the ESS is charged at time t, these constraints can be expressed as

$$\begin{aligned} P_{ps}(t) &\leq \overline{P_c}\, y_s(t) \quad (4)\\ P_{sh}(t) + P_{sg}(t) &\leq \overline{P_d}\,(1 - y_s(t)). \quad (5)\end{aligned}$$

Similarly, power cannot be simultaneously purchased from or sold to the grid:

$$\begin{aligned} P_{pg}(t) + P_{sg}(t) &\leq \overline{P_s}\, y_g(t) \quad (6)\\ P_{gh}(t) &\leq \overline{P_p}\,(1 - y_g(t)), \quad (7)\end{aligned}$$

where $\overline{P_s}$ and $\overline{P_p}$ are contractual limits and $y_g(t)$ is an additional binary variable which is equal to 1 if and only if power is injected to the grid at time t. The dynamics of the storage energy level $E(t)$ is modeled by the difference equation

$$E(t+1) = E(t) + \left[\eta_C P_{ps}(t) - \frac{1}{\eta_D}\left(P_{sh}(t) + P_{sg}(t)\right)\right]\Delta T \quad (8)$$

where η_C and η_D are the charging and discharging efficiencies. Physical limits impose that

$$0 \leq E(t) \leq C, \quad (9)$$

where C is the installed ESS capacity.

III. Receding horizon implementation

The optimization problem (1)-(9) is a mixed integer linear problem (MILP) whose solution requires the knowledge of the generation and demand profiles $P_f(t)$ and $D(t)$ over the considered time horizon. While assuming $D(t)$ to be known may be reasonable as a first approximation in a HEMS framework, $P_f(t)$ is dependent on weather conditions, and therefore highly uncertain. In this respect, this paper proposes a solution to (1)-(9) based on forecasts of PV generation and a receding horizon implementation [8]. With this approach, the problem is solved at each time t over a H-step-ahead prediction horizon using the known demand and PV generation forecasts as input data. Only the optimal power flows $P^*_{ij}(t)$ computed for the current time t are then implemented. The same procedure is repeated at time $t+1$ with updated storage level and PV generation forecasts.

Similar to what is done is [9], PV generation forecasts are not computed once, but they are updated at each time t. We denote by $\hat{P}_f(t+h|t)$, $h = 1, \ldots, H$, the forecast of $P_f(t+h)$ made at time t. In the receding horizon implementation, the forecast $\hat{P}_f(t+h|t)$ replaces the true value $P_f(t+h)$ when solving the optimization problem (1)-(9).

Remark 1: As far as PV generation forecasting is concerned, tools for predicting the power generated by solar PV plants have been developed only recently, and are still far from being a mature technology. The interested reader is referred to the survey paper [10] for a comprehensive review of different techniques and methodologies presented in the literature. ■

The choice of H is done by trading-off conflicting objectives. On the one hand, H should be as large as possible in order to fully exploit the predictive capability of the model. On the other hand, the length of the control horizon directly affects the computation time required to solve the MILP problem. In addition, the forecast uncertainty grows with H.

Given the uncertainty on future generation, it would be desirable to have the ESS available both for charging or discharging. This could be achieved by keeping the ESS energy level close to half of the storage capacity C. For this reason, the cost function in (1) is replaced with

$$C_{TOT} = C_{EC} + \gamma C_{ESS}, \tag{10}$$

where

$$C_{EC} = \frac{1}{H}\sum_{t=1}^{H}\left[r(t)P_{gh} - v(t)(P_{sg}(t) + P_{pg}(t))\right]\Delta T, \tag{11}$$

is the normalized total energy cost over the prediction horizon, and

$$C_{ESS} = \|E(H) - \frac{1}{2}C\|. \tag{12}$$

represents a terminal cost penalizing the deviation from the desired ESS energy level. In (10), the parameter γ determines the weight of the term C_{ESS} relative to C_{EC}. The tuning of γ is done by trial-and-error, taking into account its effect on (10). An advantage of using the normalized cost (11) in place of that in (1) is that this allows for the selection of γ independently of the length H of the prediction horizon.

IV. Numerical Results

Numerical results of this section are obtained using a real 5-day data set of demand, PV generation and prices from an Italian case study (see Figs. 2 and 3). The time step is $\Delta T = 5$ min. Since PV generation forecasts are not available, they are artificially simulated. The forecast $\hat{P}_f(t+h|t)$ is computed by adding to the true value $P_f(t+h)$ an error term drawn from a zero mean Normal distribution with standard deviation

$$\sigma(h) = \sigma_0(1 - e^{-\lambda h}), \tag{13}$$

where $\sigma_0 \geq 0$ and $\lambda \geq 0$ are parameters allowing to model different characteristics of forecast accuracy. The rationale behind model (13) is that forecast uncertainty typically grows with the lead time h in the short-term, and then tends to remain constant in the medium-term. A sensitivity analysis with respect to σ_0 is presented at the end of this section.

An example of how the receding horizon strategy uses the PV power and satisfies the demand, taking advantage of information about demand, generation and energy prices, is shown in Fig. 4. The first day of the data set is considered. Notice that demand is mainly satisfied with PV power during

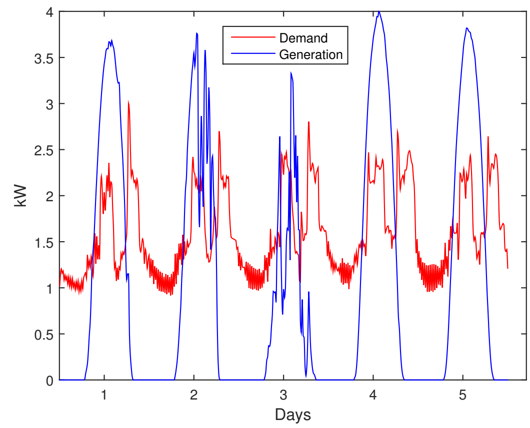

Fig. 2. Demand and PV generation profiles.

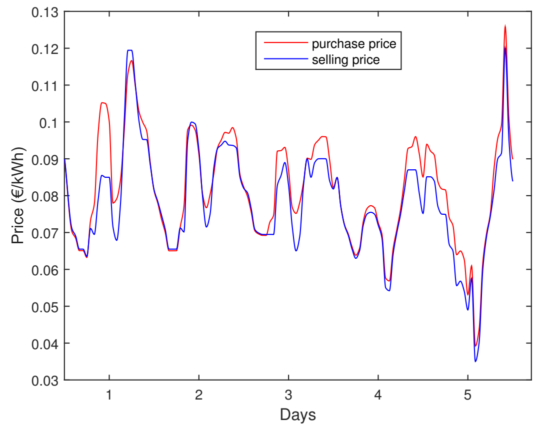

Fig. 3. Selling and purchase price profiles.

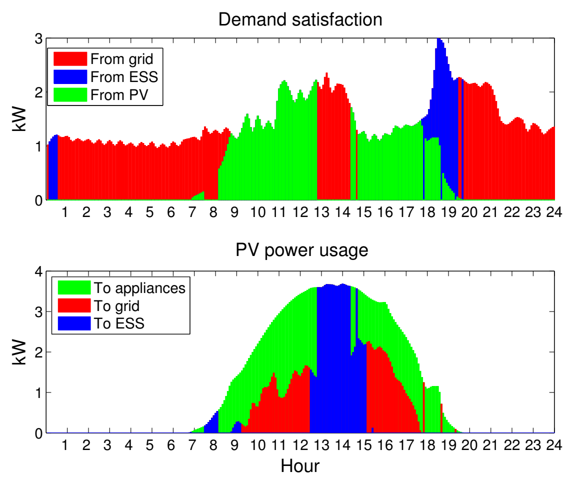

Fig. 4. Example of demand satisfaction (top) and PV power usage (bottom) with the receding horizon strategy (first day of the data set).

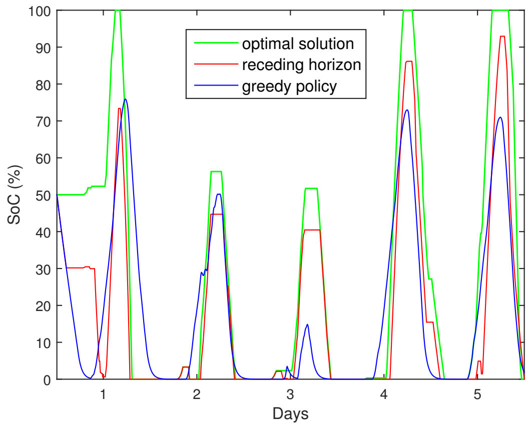

Fig. 5. ESS SoC profiles.

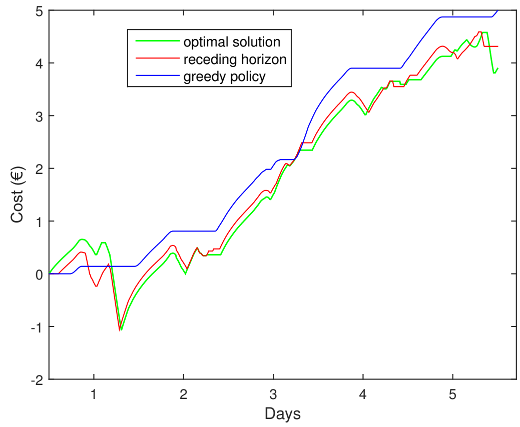

Fig. 6. Cumulative cost.

daylight hours. The only exception is between 1PM and 2PM, when the strategy prefers to supply the appliances with power from the grid, while storing PV energy into the ESS. Power from the ESS is used to supply the appliances between 6PM and 8PM. This behavior can be understood by comparing Fig. 4 with the left-hand part of Figs. 2 and 3 (day #1). Between 6PM and 8PM, PV generation is low, while demand and purchase price have a peak. Therefore, the receding horizon strategy prefers to buy power from the grid between 1PM and 2PM, when it is cheaper, and use power from the ESS between 6PM and 8PM, when it would be more expensive to buy power from the grid.

In the following, the receding horizon implementation proposed in this paper is compared with a greedy policy inspired by [11], which does not require PV generation forecasts, and is defined as follows. If $P_f(t) > D(t)$, the demand is fully satisfied by the PV power and the excess of generation is stored into the ESS, or sent to the grid when the ESS is full. If $P_f(t) \leq D(t)$, all the PV power is used to satisfy the demand, and the difference $D(t) - P_f(t)$ is drained from the ESS as long as possible, or purchased from the grid when the ESS is empty.

A. Comparison with greedy policy

The purpose of the comparison presented in this section is to evaluate to what extent the optimization-based receding horizon control policy provides better economic results than the greedy policy. The performance of both strategies is further compared with the solution of the optimization problem over the whole 5-day horizon, under the ideal scenario of known PV generation. Figures 5 and 6 show the ESS state of charge (SoC) and the cumulative cost, respectively. The receding horizon scheme is implemented with $H = 60$ (corresponding to a prediction horizon of five hours), $\sigma_0 = 0.4$ (10% of the PV installed power), $\lambda = 0.1$, and $\gamma = 0.0015$. Notice that, in Fig. 6, the cumulative cost resulting from the application of the proposed control strategy is very close to that of the optimal solution, despite being computed using uncertain PV generation forecasts.

The final cost (i.e., the total energy cost at the end of the 5-day period) incurred by the proposed strategy and the greedy policy, are 4.22 € and 5.00 €, respectively, while the optimal cost amounts to 3.90 €. This means that the receding horizon strategy yields a final cost which is only 8.2% greater than the optimal (but ideal) one, whereas the greedy policy exhibits a much worse performance (28.2% greater than the optimal one).

Notice that the control policy provided by the receding horizon scheme resembles the optimal ESS usage (see the ESS SoC profiles in Fig. 5). Looking carefully at the PV generation profiles, one may notice that the greedy policy performs fairly well in the presence of clear-sky conditions (days 1, 2, 4 and 5), whereas it degrades in cloudy day 3. This behavior is observed also in other data sets characterized by low or intermittent PV generation.

From a more in-depth study, it can be seen that there is a twofold reason for the different behavior of the two policies. First, selling power from the ESS to the grid is not allowed when using the greedy strategy. Second, PV power is always used following a fixed priority strategy, namely: $i)$ satisfy the demand; $ii)$ store energy in the ESS; $iii)$ inject power to the grid. This rigid structure does not allow, for example, to sell the excess of PV generation when the ESS is not full, or to sell all the PV generation to the grid, while satisfying the home demand with ESS only. Notice that the latter operation mode could be the most convenient one during high selling price periods. On the contrary, the receding horizon approach manages to exploit all the opportunities offered by ESS and PV generation.

B. Sensitivity analysis with respect to H and γ

Tuning of the length H of the prediction horizon and of the weighting parameter γ plays a key role for the performance of the receding horizon strategy. Figure 7 and Table I show the ESS SoC profile and the final cost for different values of H and γ. It can be observed that, for fixed γ, the final

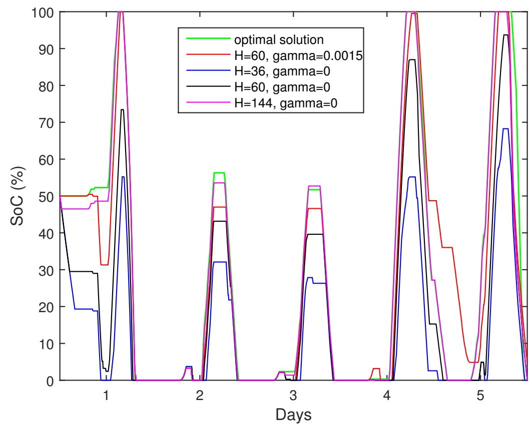

Fig. 7. ESS SoC profiles for different values of H and γ.

cost decreases while increasing H. This is likely due to the fact that, with larger H, the final time step enters earlier the prediction horizon. In this way, the final cost may benefit earlier from the predictive capability of the model.

On the other hand, the effect of γ is minor as long as γ is chosen sufficiently small (order of 10^{-3} in this case). Indeed, the best results are achieved with values of γ in the range $[10^{-4}, 10^{-3}]$. Larger values of γ may even have a negative impact on the final cost. For this reason, the choice $\gamma = 0$ will be made in the following. A similar behavior has been observed also using other data sets of both PV generation and demand.

Notice in Fig. 7 that the best results in terms of final cost are achieved by those control policies featuring a ESS usage closer to that of the optimal solution (which is actually obtained by minimizing the final cost over the whole 5-day horizon).

C. Sensitivity analysis with respect to σ_0

A further contribution of this section is to evaluate the effect of the forecast uncertainty on the performance of the proposed control strategy. Recall that, in this paper, the standard deviation of the forecast error is modelled according to (13), with σ_0 mostly affecting the steady-state accuracy of the forecasts. For the chosen value $\lambda = 0.1$, and $\Delta T = 5$ min, steady state is reached in approximately 4 hours.

Table II shows the final cost for different values of H and σ_0. In all simulations, the weight γ on the terminal cost is set to 0. It turns out that the performance of the receding horizon strategy does not seem to suffer from increasing the medium-term forecast uncertainty. The main reason is that forecasts are continuously updated at each time step, so that forecast accuracy in the very short-term is what matters most. Indeed, the results in Table II are almost insensitive to σ_0 for a given control horizon H.

TABLE I
FINAL COST (€) FOR DIFFERENT VALUES OF H AND γ ($\sigma_0 = 0.4, \lambda = 0.1$)

H \ γ	0	0.0001	0.001	0.01	0.1
12	5.350	5.343	5.344	5.725	5.821
24	4.976	4.973	4.969	5.396	5.490
48	4.430	4.429	4.428	5.071	5.155
72	4.219	4.215	4.137	4.891	4.974
108	4.040	4.039	4.237	4.824	4.907
144	4.027	4.026	4.221	4.753	4.887

V. CONCLUSIONS

This paper addressed the problem of optimal ESS management for residential customers equipped with PV generation. The proposed receding horizon approach consists in solving at each step a MILP problem with the aim of minimizing the energy bill for the end-user. A suitable cost function with a regularization term allows one to limit the size of the optimization problem, thus making the proposed control scheme amenable to a real-time implementation. Moreover, the approach is fairly robust with respect to medium-term forecast uncertainty.

The proposed ESS control strategy may be embedded in the functionalities of HEMSs. In this context, benefits of ESS and PV generation for the customer are expected to increase when coupled with the optimal management of additional devices, such as plug-in electric vehicles and smart appliances. The idea is to optimally schedule the home appliances (e.g, deferring their start or suspending their operation) to maximize the overall benefits of ESS and PV generation. Further ongoing work is focused on integrating demand response in the considered setting [12].

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TABLE II
FINAL COST (€) FOR DIFFERENT VALUES OF H AND σ_0 ($\gamma = 0$)

H \ σ_0	0.2	0.4	0.6
12	5.347	5.350	5.345
24	4.973	4.976	4.970
48	4.430	4.430	4.433
72	4.216	4.219	4.223
108	4.038	4.040	4.039
144	4.027	4.027	4.028

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