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A two-stage Energy Management System for smart buildings reducing the impact of demand uncertainty

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ABSTRACT

This paper proposes a novel two-stage Energy Management System (EMS) that is suitable for small-scale grid-connected electrical systems, such as smart homes and buildings, encompassing renewable generators and electrical storage. In such systems, forecast errors of renewable generation and energy demand profiles result in a significant uncertainty on the power exchanged between the end users and the utility grid. The proposed EMS reduces such demand uncertainty and the electricity bill for end users, at the same time. The main novelty of the proposed technique is that it does not require any change in pricing plans or user's habits, differently from classical Demand Side Management schemes. Moreover, thanks to the increased predictability of the exchanged power, utility providers are facilitated in managing the wholesale risk, for example by designing appropriate pricing schemes. The proposed EMS is based on an optimization algorithm. It starts from profiles of renewable generation and load demand, which are obtained by a forecasting method based on suitably chosen and trained Artificial Neural Networks. Furthermore, it has been designed to be suitable for an embedded implementation on low-performance processing platforms. The proposed EMS has been validated using datasets coming from monitoring campaigns. The considered case study is a smart home with an annual energy consumption of about 4500 kWh. It encompasses a grid-connected electrical distribution power plant with a 3 kW photovoltaic generator and a 4.6 kWh battery electrical storage system. The results obtained for a sample month demonstrate the effectiveness of the approach. As a matter of fact, the demand uncertainty is only 4.75% against a cumulative forecast error of 10.35% expressed as normalized root mean square error. At the same time, the end user's cash flow is 2.43% higher than the income obtained without an EMS.

1. Introduction

All the actors of the energy market need to forecast energy requests to schedule their operations accordingly. In fact, electrical energy producers must account for many constraints (e.g., generators lead times, output ranges, minimum uptime, and downtime) and to solve day-ahead unit commitment problems [1,2] to bid on the market [3,4]. For the same reason, utility providers bid on the energy market anticipating energy demand profiles [5,6]. Furthermore, the grid manager needs to plan to avoid grid reliability and stability issues [7]. However, due to uncertainty, market actors' forecasting is subject to errors, which negatively affect generation schedules, cleared bids and operation plans.

To mitigate the impact of uncertainty on their performance, market actors must account for it in their planning and bidding optimizations [8,9]. In fact, they need to take costly measures to be able to meet real-time demand deviations, like maintaining operating reserves (spinning or non-spinning) and adopting financial tools to reduce their economic risk (e.g., risk hedging) [10]. Therefore, actively reducing demand uncertainty, instead of passively accounting for it, can simplify the operations of every energy market actor and cut ancillary costs that, ultimately, are indirectly paid by end users.

The increasing integration of distributed Renewable Energy Systems (RES) adds the uncertainty of renewable energy generation to that due to user's behavior; thus, the overall demand uncertainty in terms of requested/injected power increases. In fact, the power output of RES is usually non-flat and volatile. Also, if allowed, end users and RES owners — being unaware of the consequences — tend to sell as much generated power as possible to maximize their profit.

End users' active participation is essential to improve energy efficiency, to reduce power consumption, and to reduce

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demand/supply uncertainty. However, users care for their freedom and dislike changing their habits. Therefore, they need to be involved in the issue, and they also require some incentive to behave accordingly. For this reason, Demand Side Management (DSM) programs have been proposed to engage end users in actively collaborating to maximize grid energy efficiency and to reduce overall energy consumption; examples of DSM programs are Real-time Pricing (RTP), Time of Use (TOU) pricing and Day-Ahead Retail Pricing (DAP) schemes.

Users' participation can be direct or mediated. In the first case, users must actively monitor and control their appliances, their generators output, and review utility signals to abide DSM policies. Conversely, in the latter case, users can rely on technological solutions that manage energy consumption and generation pursuing certain goals, e.g., cost reduction, response to DSM signals, energy efficiency, and demand uncertainty reduction.

Energy Management Systems (EMSs) enable end users to accomplish their energy goals and those of utility providers, starting from models or forecasting of renewable generation and load demand profiles. After processing the data, they output the operational set points and use them as a reference for local control of the electrical system devices. Several works on EMSs in technical literature explicitly avoid forecasting. In fact, they operate in real time starting from a set of rule-based operating modes corresponding to different hours of the day [11–13]. However, these approaches are incompatible with the goal of demand/supply uncertainty reduction. Other works use forecast-based optimization algorithms to schedule power flows [14–18]. However, most EMSs overlook demand uncertainty reduction as a goal, except for [17,18], which propose a two-stage approach: a day-ahead phase and a real-time phase. First, the system defines the demand/supply profile; then it minimizes deviations, which the utility bills to the user, from the defined profile. In particular, [17] controls the demand varying the thermostat set-point of the building's air-conditioning systems, but it disregards the possibility of using electric energy storage units and RES. On the other hand, [18] proposes a strategy where, after a bidding process, the system reschedules energy storage and dispatchable generators operations to minimize real-time deviations from the negotiated profile. However, it requires a demanding data exchange between the user and the utility, and it implies a change of the user's habits.

As a matter of fact, management of uncertainty and reduction of its impact are still among the major open issues in the field of EMSs [19]. Starting from a previous work [20], this paper presents a two-stage EMS for smart homes and buildings that reduces demand uncertainty while maximizing the economic convenience for the user. It is designed to manage renewable electricity generation, aggregated electrical load, and energy storage. The proposed EMS forecasts renewable generation and load demand profiles using two Artificial Neural Networks (ANNs), whose capability and performance have been previously demonstrated [21], [22].

The main novelty of this work is to propose an EMS that provides significant advantages both for the end users (optimizing their cash flow) and for the utility provider (reducing demand uncertainty). The proposed EMS is compatible with TOU and DAP DSM schemes. It is also designed to be noninvasive, since it does not require any change of user's habits, and to be easily implemented on low-performance embedded platforms. Coherently with current trends in the literature [11,19,14], the proposed system uses a Battery Energy Storage System (BESS), which is an enabling technology for the optimal exploitation of renewable generators [23]. Furthermore, several types of BESSs are technically mature and commercially available [24].

Compared with [20], this paper provides a more extensive analytic formulation of the EMS, as well as three additional analyses, i.e., the assessment of the monthly operation, of the computational requirements, and of the impact of the starting time on the algorithm's performance.

Table 1
Variables of the optimization problem.

Symbol	Description
soc	Battery state of charge
pgl	Power flowing from grid to loads
pgb	Power flowing from grid to battery
pbl	Power flowing from battery to loads
ppb	Power flowing from PV source to battery
ppl	Power flowing from PV source to loads
ppg	Power flowing from PV source to grid

The proposed technique is validated performing simulation tests in Matlab environment using data collected through monitoring campaigns. The considered case study is a smart home encompassing a grid-connected electrical distribution power plant with a photovoltaic (PV) generator and a BESS.

The paper is organized as follows. Section 2 presents the system architecture and the general formulation of the EMS. Next, Sections 3 and 4 provide details on the stages of the algorithm. Section 5 presents simulation analyses and discusses the results. Finally, Section 6 presents some concluding remarks.

2. The proposed Energy Management System

The proposed technique will be illustrated and validated referring to a smart home composed of an aggregated load, a 3 kW PV generator, a 4.6 kWh BESS, and a connection to the public grid. The case study is a single-family house (two floors, total surface 160 m^2), with four occupants and an annual average energy consumption of about 4500 kWh. To simplify the discussion the following working assumptions are made, which do not affect the general validity of the proposed EMS:

1. the aggregated load profile is considered as input; if needed, a lower-level control system can shift or schedule each load, while respecting the aggregated load profile;
2. the PV generator always works in the maximum power point for each environmental condition (solar irradiance and temperature);
3. transferring power from the battery to the grid is not allowed by the utility, following the technical rule for grid-connection in force in some European countries at the time of writing;
4. the battery must be small and affordable for the end user, so it is not suitable to sustain hours-long islanding.

With regard to point 1) the aggregated load profile refers to the user, which is ultimately the householder. Thus, the user's demand is considered as a whole, without distinguishing the contribution of each appliance. The proposed EMS must necessarily work with the house/building aggregated load profiles because it optimizes the net power flow at the exchange node with the grid. Therefore, even if specific load profiles were available, they should be aggregated.

As for point 3), removing such assumption would only imply increasing the number of variables, i.e., adding variable *pbg* to Table 1 and modifying Eqs. (5) and (6) accordingly. Moreover, the reverse power flow (i.e., grid to battery) is always allowed by the utility provider and required by the proposed EMS. The absence of this degree of freedom would limit the buffer behavior of the BESS, preventing the proposed EMS from achieving the chosen goals.

2.1. Synopsis of the EMS

Three processing stages constitute the proposed EMS, i.e., *Forecasting*, *Forecast-based Optimization* and *Local Command*, as