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Optimal battery sizing of smart home via convex programming

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A B S T R A C T

This paper develops a convex programming (CP) framework for optimal sizing and energy management of smart home with battery energy storage system (BESS) and photovoltaic (PV) power generation, for the goal of maximizing home economy, while satisfying home power demand. We analyse the historical electric energy data of three different homes located in California and Texas, and indicate the necessity and importance of a BESS. Based on the structures and system models of these smart homes, the CP problem is formulated to rapidly and efficiently solve the optimal design/control issue. Based on different time horizons, maximal powers to grid, prices of BESS, the optimal parameters of BESS and its potential to electric energy cost savings are systematically compared for the three homes. A deviation analysis between the results obtained by CP and DP (dynamic programming) is also presented.

1. Introduction

The present energy crisis (increasingly severe energy shortage and supply instability), and environmental crisis (global warming and air pollution) have promoted the rapid development of integrating renewable energy with the grid [1,2]. However, some renewable energy, such as solar and wind energy, is intermittent and unstable in nature due to metrological conditions [3,4]. Consequently, researchers have focused on developing effective control strategies to improve the performance and economy for buildings and homes integrating renewable energy [5–8]. This paper develops an optimal design/control method for battery sizing and energy management of smart home.

The existing literature, e.g., the forgoing work, has presented several optimization methods, such as mixed-integer linear programming (MILP) [9,10], rolling horizon strategy [11], particle swarm optimization (PSO) approach [12], geometric program [13], model predictive control (MPC) [14,15], dynamic programming (DP) [16], adaptive dynamic programming (ADP) [17], and stochastic dynamic programming (SDP) [18], for creating efficient operational schedules or making good consumption and production decisions to home energy management (HEM). An optimal HEM strategy under dynamic electrical and thermal constraints is developed through solving an MILP in Ref. [9], which is able to provide an optimal solution to power consumption and management of renewable resources. Similarly, considering photovoltaic (PV) arrays, battery energy storage, and electric vehicle (EV) in Ref. [10], the effects of the accurate SSUEP (Set of Sequential Uninterruptible Energy Phases)-based model on the day-ahead energy management of a residential microgrid are formulated as an MILP optimization framework. A novel energy management system based on a rolling horizon strategy for a microgrid is proposed with PV panels, two wind turbines, a diesel generator, and an energy storage system in Ref. [11]. An improved PSO approach is introduced to optimize distributed energy resources operation schedules for a smart home case study in Ref. [12]. The impacts of the response capability levels of consumers on the economic integration of distributed PV power in smart homes, and the impacts of PV and battery capacities on consumers power expenses are analyzed using non-cooperation game theoretical power market complementarity model in Ref. [13]. Based on short-term forecasts of residential renewable power generation, a dynamic HEM algorithm is put forward in Ref. [14] for decreasing the total grid energy cost while maximizing user comfort. Both simulation and experimental results show the ability of the devised algorithm to control both sources and loads. A nonlinear predictive

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energy management method for buildings with PV system and battery storage is proposed in Ref. [15], which forecasted house load demand via artificial neural networks. Based on highly resolved energy consumption models, an automated dynamic energy management framework is established in Ref. [16] to find the optimal schedule of residential controllable appliances, where DP is utilized to find the global solution. A computationally feasible and self-learning optimal control scheme for a residential energy system with batteries is devised in Ref. [17], the idea of which is to approximate DP solution by using neural networks. A probability distribution model combining household power consumption, EV home-charging, and PV power production is built using a convolution approach to merge three separate existing probability distribution models in Ref. [18]. In Ref. [4], ZigBee technologies are exploited for comprehensive field tests, including monitoring PV and wind energy systems, and energy management of buildings/homes. The literature provides a number of approaches for energy management of smart home with renewable energy, almost all of which share a common goal, namely, to meet overall home electric power demand while minimizing the total operational energy cost. Few studies explored the optimal battery size and control strategy simultaneously. Furthermore, a single home was often considered without a comparision of multiple homes with different electricity supply/demand patterns.

This paper constructs an optimal design/control framework for exploring multiple smart homes with battery energy storage system (BESS) and PV arrays power generation. The key challenge addressed by this paper is to simultaneously optimize the battery size and energy management strategy with the consideration of the cost of BESS, computational efficiency, and home electricity difference. An emerging effective tool, convex programming (CP), which can rapidly and efficiently optimize both management strategy and parameters, as opposed to many other methods generally focusing on only controls, has been applied by researchers [19–21]. Demand response (DR) implementation considering a single home with different appliances is modeled using CP to minimize electricity payment in Ref. [22]. Similarly, A later study in Ref. [23] formulates a CP problem to minimize electricity payment and waiting time under real-time pricing for a multi-agent system, in order to evaluate optimal residential DR implementation in a distribution network. The previous two studies, however, do not involve optimal component design. Nevertheless, CP has been successfully applied to simultaneously optimize component size and energy controller for vehicles [24,25]. In this article, CP is leveraged to rapidly and efficiently optimize both HEM strategy and BESS size. In our previous study [26], a CP framework was built for the optimal integration of a hybrid solar-battery power source into smart home nanogrid with PEV load. The main differences between this endeavor and [26] (i.e., major contributions) include (i) the optimization results of three different homes with PV arrays located in California and Texas are systematically compared, instead of analyzing a single home in most of existing studies, and (ii) a deviation analysis between the outcomes procured by CP and DP is carried out to showcase the computational efficiency and effectiveness of CP.

The remainder of the paper is arranged as follows. Section 2 analyses the historical electric energy data of the three homes. The structures and models are described in Section 3. The CP problem is formulated in Section 4. The optimization results are discussed and contrasted in Section 5, followed by conclusions summarized in Section 6.

2. Historical data analysis

In order to reduce the cost of electric energy and carbon emissions, residents are seriously concerned about installing PV panels on the roof of their houses, especially in the area with high electricity price and abundant sunshine, i.e., California, USA. Due to the high price of battery, some of the residents only stall PV arrays without BESS. They directly sell the redundant PV power to the utility grid, since PV cannot storage energy by itself.

We analyse the PV power supply data and home load data from three different family homes with PV arrays. The collected data of Home 1 correspond to date range from 2014-01-01 to 2014-12-31 in California, US [27]. The collected data of Home 2 and Home 3 correspond to date range from 2016-01-01 to 2016-12-31 accessed from the Pecan Street Inc. Dataport [28]. The hourly grid power (the home load power minus the PV power) of the three homes on each day, as well as their averages, are shown in Fig. 1. The hourly grid power of the three homes vary from −2.26 kW to 4.58 kW, −4.26 kW to 7.42 kW, and −3.37 kW to 7.07 kW, respectively. The peak power to the grid of the three homes always happen from 10:00–14:00, 8:00–17:00, and 10:00–18:00, respectively, owing to the PV power generation. The peak power from the grid always occurs from 18:00–1:00 for Home 1, from 17:00–24:00 for Home 2, from 6:00–9:00 and 17:00–23:00 for Home 3, due to the heavy home load demand.

At present, there are two types of electric rate plans for residential houses from Pacific Gas and Electric (PG&E) Company in California, tiered rated plan and time-of-use rate plan. Referring to the non-tiered, time-of-use plans, the hourly time-varying electric price in California, as well as that in Austin, Texas, is shown in Fig. 2-(a) [29–32]. The PG&E electric price is lowest (10 cents/kWh) from 23:00 to 7:00, and more expensive during Peak (43 cents/kWh, 14:00–21:00) and Partial-Peak (22 cents/kWh, 7:00–14:00 and 21:00–23:00) periods. The Austin Energy electric price is lowest (2.18 cents/kWh) from 22:00 to 6:00, and more expensive on Peak (12.2 cents/kWh, 14:00–20:00) and Mild-Peak (7.13 cents/kWh, 6:00–14:00 and 20:00–22:00) hours. Obviously, the PG&E electric price is more expensive than the Austin Energy price. Fig. 2-(b to d) plot the hourly electric energy costs for the three homes in one year on each day and its average [29–33]. It is evident that all the three houses sell electric energy to the grid during Partial-Peak period and buy it during Peak period. If having a BESS, users can store the redundant PV power and buy electric energy with low price for the use of Peak period. The BESS can not only reduce household electric cost, but also supply electric power to the house during lacking of electric power, because of blackout [26]. Next, we apply CP approach to design the main parameters of BESS and synthesize an energy management controller.

3. Configuration and models

3.1. Configuration

We consider a single smart home with BESS and PV arrays, as illustrated in Fig. 3 [26,34]. The smart home electric energy system comprises house appliances, utility grid, a home BESS, PV arrays, and associated power electronics. The power flow among them is managed by a smart home energy management system (SHEMS). Because the original house has had the PV arrays, but without BESS, an important mission is to determine desired parameters of the home BESS.

3.2. System model

The power balance equation of the smart home with home BESS and PV power supply is