Applied Energy 254 (2019) 113630

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Concurrent optimization of thermal and electric storage in commercial buildings to reduce operating cost and demand peaks under time-of-use tariffs

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HIGHLIGHTS

- Market-tariff-induced DSM can reduce electric grid stress and emissions.
- We introduce a novel DSM framework that uses one-day-ahead weather forecasts.
- Framework optimizes temperature setpoints and battery dispatch in real time.
- Peak loads and electric bills reduced substantially.
- Results imply substantial grid stress alleviation for urban environments.

ARTICLE INFO

Keywords:
Smart grid
Grid-efficient building
Building energy modeling
Demand response
Energy storage
Time-of-use tariff
Pre-cooling
Battery dispatch
Demand-side management
Real-time control optimization
Particle swarm optimization

ABSTRACT

Demand-side management (DSM) in response to market-based electricity tariffs can potentially increase the efficiency and reliability of the electric power grid. This study introduces a novel, one-day-ahead DSM framework which optimizes temperature setpoints and battery dispatch in office buildings, subject to a time-varying and/or demand-based electricity tariff. To reflect real world implementation, our framework operates in two-steps. First, during the passive, battery-only DSM optimization, historical weather and electricity load data for a given building are used to determine its optimal battery capacity. Second, once the battery has been installed, a one-day-ahead, real-time DSM algorithm optimizes both the building's daily temperature setpoints and the battery's charge/discharge pattern. The optimization objective is to minimize the total operating cost (tariff charges and battery system) while still satisfying occupants' thermal comfort. Using a case study with a medium-fidelity electric load model for a standard office building, the performance of the proposed framework is validated by quantifying savings in operating cost, reduction of monthly grid peak loads, and the achieved human occupant comfort. To illustrate the advantage of optimizing temperature setpoints and battery dispatch concurrently, the combined performance is compared with that achieved by standalone DSM (i.e., using only battery dispatch or only temperature setpoints). We found that concurrent optimization can reduce a building's monthly peak demand on the grid by up to 26%. Electricity tariff charges are reduced by 11%, more than is required to offset storage costs, thus providing an overall profit to building operators who use such DSM. Payback time is approximately 5 years.

1. Introduction

1.1. Overview

High electric loads in buildings at certain times of the day, also referred to as peak demands, place great stress on the electricity grid and require environmentally and economically inefficient peak generation capacity to meet these peak demands [1]. As such, up to 20% of the total installed electricity generation capacity in the United States is dedicated to meeting peak demands (defined as in use only 5% of the time) [2]. The building sector contributes up to 75% of all electricity usage and is a disproportionally large contributor to peak demand [3]. Market-based time-of-use tariffs that incentivize demand-side management techniques (DSM) [4–6], together with the integration of electricity storage systems [7], can play an essential role in reducing peak demands and thus increasing the efficiency and reliability of the grid.

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https://doi.org/10.1016/j.apenergy.2019.113630
Received 25 December 2018; Received in revised form 11 July 2019; Accepted 29 July 2019

Here, we focus on commercial building DSM with one-day-ahead optimization of both the building's air conditioning (e.g., pre-cooling) and battery dispatch (e.g., charging during off-peak times to use during peak times). The objective is to achieve superior peak load reduction while also reducing the building's electricity bill enough to fully offset required battery costs, thus leading to lower overall costs for building operators.

1.2. Context of prior DSM studies

DSM, here defined as deliberate changes in electric load profiles in order to lower tariff costs and grid stress, can be achieved through the application of a variety of techniques, including [8,9]: (i) *direct-load control technique* in which a utility operator remotely controls customers' electrical equipment (e.g., heating and cooling loads) on short notice to reduce peak load [10]; (ii) *load limiter technique* in which the customer agrees to react to peak load by limiting their total electricity usage [11]; (iii) *price-based* (e.g., *ToU*) *technique* in which the electricity cost is set high at peak load time and low at off-peak time, to encourage customers to engage in load management. In this last technique, ToU electricity cost is usually designed to reflect the utility's investment cost structure. Load management refers to different approaches that control or schedule curtailable and deferrable loads (e.g., changing the temperature set points of air conditioners, dimming lighting, or charging electric vehicles), using building automation systems to achieve demand load reduction (load shaving) and/or load shifting (e.g., shifting the demand to the low-price periods) in buildings [12]. Such load management via modifying temperature setpoints, e.g., by pre-cooling the building already in the early morning hours before occupants arrive, essentially makes use of the thermal energy storage provided by the building's envelope and inner structure. Load management can also be achieved by strategically dispatching on-site electricity storage [7].

DSM can be mathematically formulated through the concept of model predictive control (MPC) [13]. In this context, MPC is a mathematical optimization procedure to minimize the building's peak load on the grid, the electricity cost, and the life cycle cost of equipment while satisfying predefined constraints such as human comfort and operating characteristics of building equipment and storage systems. Different optimization formulations and algorithms have been applied for DSM [14–16]. Among them, Logenthiran et al. [15] formulated a generalized DSM load management technique using a heuristic-based Evolutionary Algorithm (EA). The main objective of this technique is to reduce the cost of electricity (the utility bill) and the peak load demand in a future smart grid by scheduling deferrable devices (e.g., water heater, clothes dryer, coffeemaker, oven, and lights) in commercial, residential, and industrial buildings. Although substantial savings have been reported using the proposed technique, human comfort and the actual tariff structure were not considered in this study. Chen et al. [17] developed a new one-day-ahead demand-side algorithm for large-scale data centers using a mixed-integer linear programming (MILP) formulation. The algorithm minimizes the total electricity cost and improves the environmental impacts by optimally shifting cloud service tasks among distributed data centers.

Over the last two decades, the applicability of DSM techniques has been improved by integrating energy storage systems (ESS) in a distributed fashion [14,18–21]. Storage-based DSM enables peak grid load management without curtailing the actual energy use of the building systems themselves. In this case, the electricity cost variation (price-based DSM) can be exploited to charge the storage at time of low electricity cost and then later use the stored energy during peak demand [22]. Many different such storage options are available, including electrical and thermal energy storage [23,24]. Several research studies have analyzed the economic viability of implementing storage-based DSM under different tariff structures in commercial or residential buildings (e.g., [25,26]).

While there has been substantial research on optimizing the energy consumption and peak demand through model predictive control (MPC) algorithms, relatively few of them have focused on approaches for adjusting zone setpoint temperature that give near-optimal performance in reducing the peak load (e.g., [8,27]). Ma et al. [28] used a min-max algorithm and ToU tariff structure to reduce electricity supply (kWh) and demand (kW) costs in a single-story commercial building by controlling the zone temperature in different time periods. In this study, a fixed, predefined temperature range was used as a thermal comfort constraint for the five temperature variables in the control algorithm. The researchers showed that this MPC-based algorithm can achieve superior performance in saving electrical costs compared with more basic zone temperature adjusting approaches. Considering the high dependency of the real-time comfort model on inside/outside temperature and humidity, radiant temperature, and human activity level [29], the level of simplification of their thermal comfort model may limit applicability of this formulation in real world applications.

1.3. Specific motivation and differentiation of this study

We have previously shown, for the residential sector, that adding a battery to a building can modify its electric load profile on the grid such that the electricity costs under a typical tariff with both time-of-use and demand charge characteristics can be reduced to more than offset the battery system cost (purchase, installation, and financing), thus reducing the building's overall operating cost on one hand and the building's contribution to grid peak demands on the other [22,26]. A similar modeling framework has since been applied to determine the breakeven costs of a battery system for commercial buildings on the same tariff [30]. In such studies, the actual electricity use of the building itself (appliances, plug loads, HVAC, etc.) is not changed, however the use of the battery enables a smoothing of the load profile that is passed on to the grid. In commercial buildings, building automation systems (BAS) to e.g., automatically dim lights and smooth day time demand via pre-cooling can achieve significant benefits by optimizing the electricity use of the building itself – i.e., employing only thermal energy storage in form of the building envelope itself, however not electricity storage.

Building on above work, in the present study, we investigate whether (i) employing both thermal storage (via pre-cooling) and electrical storage can lead to steeper cost and peak demand reductions than any one storage alone; and (ii) whether such concurrent optimization can be carried out fast enough in order to employ such framework in real time, for a typical office building, battery technology, and tariff structure.

In line with this rationale, the proposed DSM approach has the following novel characteristics:

(a) *Concurrent optimization of inside air temperature and dispatch strategy of the electricity storage system*: Several studies explored the advantages of price-based DSM in scheduling storage or controlling ventilation or air-conditioning of interior spaces (e.g., adjusting zone setpoint temperature) in commercial buildings (e.g., [28]). However, to the best of our knowledge, there have been no reported studies involving a combination of electricity storage-based DSM and DSM based on setpoint temperature optimization. This study concurrently optimizes the daily temperature setpoints and the storage dispatch using a bi-level optimization approach.

(b) *Weather-based computationally efficient control of temperature set points*: In the current paradigms in DSM based on controlling setpoint temperature, the variation of temperature setpoints is limited to be between lower and upper bounds of comfort and follows a fixed, predefined trajectory for different seasons. In this study, the daily setpoint temperature profiles are improved by using B-splines that are tuned via hourly temperature control points. This formulation offers greater flexibility in representing different arbitrary trajectories in the daily setpoint temperature optimization, especially when real-time thermal comfort constraints must be considered. The resulting computational efficiency allows for real-time

Algorithm 1: Real-time DSM optimization

for $d = 1$ *to* D **do**
  Initialize: ${}^{\mathrm{d}}\mathrm{X}^{*}_{\mathrm{TEMP}} = \mathrm{X}_{\mathrm{TEMP}}$ based on ASHRAE Standard-55 [5]
  $Q^{+}_{m} = \max\limits_{k \subset T^{m}} \{G_k\};\ k \in \mathbb{Z}_{>0}, and\ k \leq N^{d-1}$
  $Q^{d}_{m} = \max\limits_{k \subset T^{m}} \{E_k({}^{d}X^{*}_{TEMP})\};\ k \in \mathbb{Z}_{>0}, and\ N^{d-1} < k \leq N^{d}$
  if $\exists m \mid Q^{d}_{m} > Q^{+}_{m}$ **then**
    ${}^{\mathrm{d}}\mathrm{X}^{*}_{\mathrm{TEMP}} = argmin(\mathbb{H}(\mathrm{X}_{\mathrm{TEMP}}))$
    subject to: $\mathrm{X}^{\mathrm{lb}}_{\mathrm{TEMP}} \leq \mathrm{X}_{\mathrm{TEMP}} \leq \mathrm{X}^{\mathrm{ub}}_{\mathrm{TEMP}}$
    Occupancy comfort constraints
  else if $\mathrm{r}_{\mathrm{e},0} \times \eta^{2}_{\mathrm{C/D}} >> \mathrm{r}_{\mathrm{e},1}$ **then**
    Storage-based DSM:
    $\mathbb{H}(\mathrm{X}_{\mathrm{TEMP}})$; $\mathrm{X}_{\mathrm{TEMP}}$ based on ASHRAE Standard-55
  else
    Non-DSM, and $\mathrm{X}_{\mathrm{TEMP}}$ based on ASHRAE Standard-55
  end
end

Fig. 1. Pseudo code representation of the real-time DSM optimization to find the optimum temperature setpoints and battery charge/discharge profiles.

optimization of temperature setpoints and battery dispatch based on one-day-ahead weather forecasts (temperature, humidity, wind speed/direction, and solar irradiance).

(c) *Flexible electricity tariff structure:* The unique formulation of the real-time DSM algorithms in this proposed framework makes it independent of the available price-based DSM programs. For the case study, we use an actual commercial building electricity tariff for New York City.

2. Data and Methods

A general overview of the design and its rationale of the framework is given in Section 3.1. Section 2 is organized as follows: The basic framework of both a passive and a real-time optimization (steps 1 and 2 in Fig. 4) were developed to be universally applicable for any building subject to any ToU and/or demand-based tariff and are therefore explained first (Sections 2.1 and 2.2). Following that are descriptions of the specific models and parameters used in the case study, namely the particle swarm optimization (PSO), the battery model, the electricity tariff, the model for the electricity consumption of the office building, and finally the human thermal comfort model (Sections 2.3 through 2.7, respectively).

2.1. Passive DSM optimization algorithm

The Passive DSM optimization is performed to obtain the optimal capacity of battery storage by maximizing the annual profit of implementing electric storage-based DSM on historical load data. The annual profit herein is defined as the annual tariff charge reduction minus annualized cost for battery equipment, installation, and financing. Qualitatively, the optimization evaluates the following tradeoffs: Higher capacity allows for more pronounced reduction of peak grid loads thus reducing demand charges in the tariff, charged per kW. However, higher capacity also increases equipment costs and energy losses due to round-trip inefficiencies, thus increasing the energy charges in the tariff, charged per kWh (Section 2.5). Quantitatively, the passive DSM optimization is formulated as a bi-level mixed-integer nonlinear programming (MINLP) problem. The bi-level optimization [31] was chosen in order to reduce the computational cost [32,33]. The general form of this MINLP problem can be expressed as:

$$\begin{aligned} &\Lambda^{*} = argmax\left(\textstyle\sum_{n=1}^{12} \left[\mathbb{P}(G_n^{w/o}) - \mathbb{R}(\Lambda) - \mathbb{P}(G_n^{w}(\Gamma_n^{*},\ \Lambda))\right]\right)\\ &subject\ \ to: \Lambda \in \mathbb{Z}_{>0},\quad \Lambda \leq \Lambda^{max}\\ &where: \quad \Gamma_n^{*} = argmax(\mathbb{P}(G_n^{w/o}) - \mathbb{R}(\Lambda) - \mathbb{P}(G_n^{w}(\Gamma_n,\ \Lambda)))\\ &\qquad subject\ \ to: \ \ Battery\ \ storage\ \ system\ \ constraints \end{aligned} \tag{1}$$

where $G_n^{w/o}$ and G_n^{w}, respectively, represent the non-DSM and the storage-based DSM grid loads in month *n*; and *R* and *P* represent the monthly storage equipment cost (Section 2.4) and the electricity cost function (Section 2.5), respectively. Λ is an integer design variable in the upper-level optimization and denotes the size (or capacity) of storage; and Γ_n^{*} is the optimal demand limit vector obtained by the lower-level optimization, as formulated in Eq. (1). The concept of demand limits and their effect on battery dispatch (i.e., when to (dis-)charge) is the same as we described previously [26]. Γ_n is a continuous design vector with a dimension equal to the number of time periods in the ToU tariff structure. The constraints related to the battery storage system are explained in Section 2.5.

2.2. Real-time DSM optimization

The purpose of the real-time DSM optimization is to minimize the electricity cost by adjusting the grid demand limits (which in turn govern battery charging/dis-charging; see Section 2.1) while satisfying battery constraints and by adjusting the temperature setpoints while satisfying the human comfort constraints. The electricity cost is governed by: (i) the one-day-ahead setpoint temperature profiles and thus resulting load profiles for air conditioning and fans (for each zone in the building); and (ii) the one-day-ahead dispatch strategy of the battery and thus how much of the load profiles are drawn from the grid versus the battery.

Fig. 1 shows a pseudo-code representation of this optimization (Algorithm 1). Its elements are as follows: For every day d in the billing period (Section 2.5), the daily setpoint temperature profile is defined using a B-spline, which is updated through a daily temperature design vector (${}^{d}X_{TEMP}$) that consists of temperature control points (one per hour; bound between 18 and 26 °C). The purpose of using this particular formulation is to reach maximum flexibility in defining setpoint temperature (and hence prevent the possibility of obtaining suboptimal setpoint temperatures) while still keeping computation time for the optimization feasible for real-world implementation (where the optimization for each day would have to complete during the night before). In order to reduce computation time, for each day in the billing period, the optimization is performed only *IF* the predicted daily peak

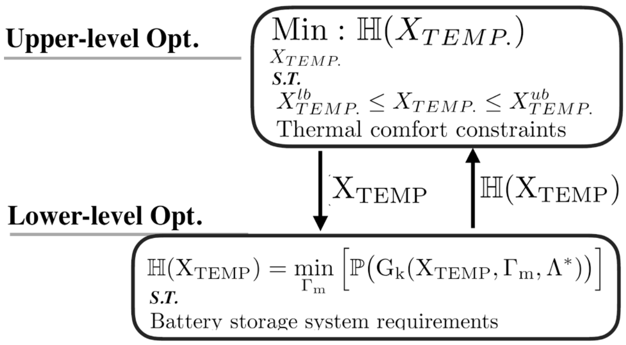

Fig. 2. Bi-level optimization in predictive, real-time DSM formulation.

electricity consumption ($Q_m{}^d$) surpasses the maximum grid loads until the dth day ($Q_m{}^+$) in any ToU time period, m = 1,2,…,M, of that day (Section 2.5), i.e., $\exists\ m | Q_m^d > Q_m^+$ (see Section 3 for details and rationale). In Fig. 1, G_k and E_k are the average grid load and the average electrical load (in kW) in stage k, respectively. Denoting the time interval in a tariff structure by Δt (in hours), the stages on the dth day are defined as:

$$k \in [N^{d-1}+1,\ N^{d-1}+2, \cdots,\ \ N^{d-1}+24/\Delta t], \qquad N^d = \frac{24 \cdot d}{\Delta t}, \qquad N^0 = 0 \tag{2}$$

In the $Q_m{}^d$ formulation, E_k subject to $N^{d-1} < k \leq N^d$ is the predicted electricity consumption through the dth day when fixed setpoint temperatures based on the ASHRAE Standard are used [34]. The $Q_m{}^+$ formulation, G_k subject to $1 < k \leq N^{d-1}$ is the grid load (after DSM action) until the dth day.

The concurrent one-day-ahead optimization of the setpoint temperature profile and demand limits is formulated as a bi-level optimization [31] (Fig. 2) in order to reduce the computational cost and mitigate the uncertainty in the results of the real-time optimizer [32]. A one day-ahead optimization for the case study building took 80 min on a standard desktop computer with 2.5 GHz Intel Core i5 CPU and 8 GB memory (Section 4).

In the upper-level formulation, the temperature optimization is performed to determine the optimal temperature setpoints for each zone (${}^dX^*_{TEMP}$), while satisfying the side constraints on a design vector and the human comfort constraints. Although human comfort is related to several factors including lighting, temperature and air quality, in the case study only the thermal comfort is considered as explained in Section 2.7. As illustrated in Fig. 2, for each design candidate X_{TEMP}, a lower-level optimization is performed to minimize the electricity cost and obtain the optimal battery strategy, as given by:

$$\mathbb{H}(X_{TEMP}) = \min_{\Gamma_m} [\mathbb{P}(G_k(X_{TEMP},\ \ \Gamma_m,\ \ \Lambda^*))]$$

$$where: \quad m = 1, 2, \cdots, M;\ k \in \mathbb{Z}_{>0}; \quad and \quad N^{d-1} < k \leq N^d \tag{3}$$

$$subject\ \ to: \begin{cases} \Gamma_m > 0 \ \ if \ \ r_{e,0} \cdot \eta_{C/D}^2 \gg r_{e,1} \\ \Gamma_m > Q_m^+ \ \ if \ \ r_{e,0} \cdot \eta_{C/D}^2 \lesssim r_{e,1} \\ and \quad battery \quad storage \quad system \quad constraints \end{cases}$$

where P represents the electricity cost function (Section 2.5), Λ^* denotes the optimal storage capacity determined in the passive DSM optimization (Section 2.1), and $\Gamma_{m=1,2,\ldots,M}$ is an M-dimensional design variable in the lower-level optimization which denotes demand limits in the M different ToU time periods.

Eq. (3), in order to define the lower bounds on demand limits, differentiates between two parameter regimes related to the tariff: (i) the electricity rate per unit of energy (in \$/kWh) in the on-peak period, $r_{e,0}$, multiplied by the square of charging/discharging efficiency, $\eta_{C,D}$, is much larger than the energy rate in the off-peak period, $r_{e,1}$; and (ii) otherwise. In the first regime, the maximum available battery capacity can be exploited while satisfying battery constraints (Section 2.4). In the second regime, the demand limits are bound by the maximum peak grid loads until the dth day (i.e., $\Gamma_m \geq Q_m{}^+$). The first regime will result in significantly more charging-discharging cycles per month which affects battery life and thus the monthly storage cost. For every day in the billing period in which the predicted daily peak electricity consumptions, $Q_m{}^d$, are lower than the maximum peak grid loads until the dth day, the two regimes are reflected in Algorithm 1 as follows: In case of the first regime, the real-time battery dispatch strategy optimization (Eq. (3)) will be performed and the setpoint temperatures will be fixed to those from the ASHRAE Standard [34]. In case of the second regime, DSM will not be performed (but the setpoint temperatures fixed to those from the ASHRAE Standard).

2.3. Particle swarm optimization (PSO)

Originally developed by Kennedy and Eberhart in 1995 [35], PSO algorithms have been widely used in MPC to improve thermal comfort, minimize energy consumption, and reduce the life cycle cost of equipment systems (e.g., [36–38]). In our study, one particular implementation of the PSO, called Mixed-Discrete PSO (MDPSO), which was developed by Chowdhury et al. [39], is used in the Passive and Real-time DSM optimization algorithms. The advantages that the MDPSO algorithm provides over the conventional PSO algorithm include: (i) an ability to deal with both discrete and continuous design variables, and (ii) an explicit diversity preservation capability that mitigates the possibility of premature stagnation of particles [40].

2.4. Battery model and cost used in case study

We use the same modeling framework for battery charge, discharge, lifetime and cost as set forth in Zheng et al. [26], and assume the parameter set for the ZnMg dioxide chemistry (because of its superior economics in in that study). Briefly, the model assumes a nominal capacity (Λ, determined upfront via the passive DSM), a time-dependent state of charge (SoC), a maximum allowed depth of discharge (90%), 3 charging modes (charge or discharge at 1C rate or idle, with respective on/off times determined by the real-time DSM) with an AC/DC inverter efficiency of 95%, and a round trip charge/discharge efficiency of $\eta_R = (\eta_{C/D})^2 = 80\%$. The battery needs to be replaced (200 US\$ per kWh nominal) each time either 4000 full cycles are reached or 15 years have passed (installation cost US\$2000). Battery purchase, installation, and financing cost (10%) are then converted into a constant monthly battery system cost. In addition, we quantify a simple system payback time (in years), estimated as the purchase plus installation cost divided by the annual reduction in electricity tariff cost that is achieved by DSM. Note that this estimate assumes that the annual tariff reduction over multiple years is similar to that we determined for 2014 (i.e., assumes similar weather in subsequent years).

2.5. ToU demand-based tariff used in case study

A ToU tariff is a utility rate structure, which divides a day (and/or a week) into different time periods, governed by different electricity costs. For large users such as office buildings, a typical ToU tariff includes not only energy charges (P^{EC}, charged per kWh) but also demand charges (P^{DC}, per kW) which are determined according to the peak demand, typically measured over 30 min windows. Such tariffs are designed to incentivise both load shifting (i.e., consuming electricity during off peak times, here to charge the battery or to pre-cool the building) and the reduction of temporary demand peaks during the day (here by exploiting the battery and the building's thermal envelope storage). In order to make the case study as realistic as possible, we use New York City's Commercial Building tariff SC9 which is described in detail in Zheng et al. [26] and was recently further characterized in a related study to determine break-even battery costs for DSM without