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A hierarchical scheduling and control strategy for thermal energy storage systems

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ABSTRACT

Energy storage in buildings is an important component of peak shifting and load leveling strategies devised to improve the operation of the electric grid. Maximizing the load-leveling benefits afforded by both active and passive thermal energy storage (TES) requires coordinating the charge/discharge events with external factors, such as weather, occupancy, and time-of-use pricing. The development of such controllers (typically following the model predictive control (MPC) paradigm) is challenging owing to the dimensions and multiple time scale nature of the problem. In this work, we propose a hierarchical control strategy, comprising a dynamic scheduling problem for managing active TES in the slow time scale, and a control scheme with a shorter horizon for managing passive TES in the fast time scale. The approach is demonstrated through an application to a TES system with phase change material (PCM), which presents unique modeling challenges. The proposed formulation and solution strategy allow for obtaining solutions in real time. Moreover, it is shown that the proposed approach leads to significant cost savings, outperforming (reasonable) operating heuristics even under uncertainty in forecasting building loads.

1. Introduction

Over 70% of the electricity use in the US can be attributed to commercial and residential buildings [1]. In addition to being large electricity consumers, buildings use power at a variable rate over the course of a day. In general, demand from buildings exhibits a peak in the afternoon hours. Electricity producers and grid operators resort to spare generation capacity (referred to as "peaking plants") to meet this temporary demand rise, often incurring additional economic and environmental costs [2]. Demand response (DR) strategies aim to alter the electricity demand pattern of buildings [3], typically focusing on "load leveling," i.e., lowering peak demand and distributing power requirements more evenly during the day.

Energy storage is an important component of peak shifting and load leveling strategies: energy can be generated in excess of demand and stored during off-peak hours, and used to supplement the generation capacity during peak times. In this manner, generators can operate at or close to their peak efficiency. Evidently, the use of energy storage for load leveling purposes is dependent on the availability of an energy storage facility of adequate capacity. At present, grid-level installations of storage batteries are cost-prohibitive, and efforts have concentrated on using storage to modulate the energy use of large consumers. Since HVAC systems account for over 20% of the energy use of buildings [1], they have become primary targets for load leveling initiatives.

Thermal energy storage (TES) technologies provide a viable and cost-effective means of shifting electricity demands for HVAC loads. In particular, residential and commercial buildings offer multiple means of thermal energy storage. On the one hand, structural elements (walls, foundations and foundation slabs, floors, etc.) in some building designs constitute a significant thermal mass that can be used to retain and release energy [4–6]. Additionally, heating, ventilation and air conditioning (HVAC) systems can be designed or retrofitted with tanks that store cooling or heating agents (e.g., chilled or hot water) to help improve operating efficiency and flexibility [7,8]. Notably in the case of a predominantly cooling climate (i.e., in hot weather), building HVAC systems can be operated in a pre-cooling mode, where the structure is cooled beyond the usual limit during the (morning) off-peak hours; in turn, this allows the HVAC system to operate at lower intensity during the peak (afternoon) hours. Storage tanks are also typically charged at night, and the chilled water is used to supplement HVAC operation at peak times.

Maximizing the load-leveling benefits afforded by building thermal energy storage does, however, require a close coordination of

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Nomenclature

$Charge(t)$	state of charge of the PCM tank
$C(t)$	time-varying price schedule
$F_{1b}(t)$	flow recycled to the chiller
$F_2(t)$	flow before the split at valve 1
$F_3(t)$	flow to the cooling coil
$F_4(t)$	flow to the storage tank
$H_{pcm}(t, z, x)$	enthalpy of the PCM
$k(t, z, x)$	conductivity of the PCM
$m_i(t)$	operating modes of the coolant loop (i = 1, 2, 3, 4)
$P_{HVAC}(t)$	electricity consumption in the chiller
$Q_{chill}(t)$	heat removed by the chiller
$Q_{pcm}(t, z)$	heat transfer between the PCM and coolant
$Q_{bldg}(t)$	load removed by the cooling from the building
$s(t, z, x)$	solid fraction of the PCM
S	cyclical schedule of operating modes
$T_{chill}(t)$	chiller temperature
$T_{cc}(t)$	cooling coil temperature
$T_{tank}(t, z)$	temperature of coolant in the tank
$T_{pcm}(t, z, x)$	temperature of the PCM
$T^{SP}_{chill}(t)$	chiller setpoint temperature
$v(t)$	velocity of coolant in the tank
$\mathbf{x}_B$	building dynamic variables (e.g., indoor air temperature)
$\mathbf{u}_P$	continuous decision variables within the air side of the HVAC system
$\mathbf{m}_P$	operating modes within the air side of the HVAC system (e.g., Table 1)
$\mathbf{x}_P$	states in the air side of the HVAC system
$\mathbf{u}_A$	continuous decision variables within the coolant side of the HVAC system
$\mathbf{m}_A$	operating modes within the coolant side of the HVAC system
$\mathbf{x}_A$	states in the coolant side of the HVAC system
x^{SP}_{A}	setpoints in the coolant side of the HVAC system
$\mathbf{d}$	disturbances to the system (e.g., outdoor air temperature, occupants)
t_0	start time of the horizon
T	prediction horizon length
T_p	horizon of price forecast
T^{slow}	prediction horizon in the TES scheduling calculation
T^{fast}	prediction horizon in the fast MPC

the charge/discharge events with external factors such as grid load (which, in turn, dictates energy prices in real-time price structures), weather, and building occupancy. This, in turn, calls for the development of advanced optimization-based control strategies, which are capable of orchestrating the operation of the HVAC system and TES elements under the uncertainty provided by the aforementioned factors.

In this paper, we introduce a framework for developing such energy management strategies. Both "active" (e.g., storage tanks) and "passive" (e.g., building structural elements) TES systems are considered, with a particular emphasis on the use of *latent* active storage based on phase change materials (PCMs). A case study involving latent energy storage is presented, which poses interesting challenges for the controller design due to the nonlinearities associated with phase change behavior. The paper is organized as follows: in the next section, a review of optimization-based strategies for managing building energy use and associated challenges is presented. We highlight the novel aspects of our approach at the end of Section 2. Next, a hierarchical energy management framework is proposed in Section 3. This is followed by a detailed case study in Section 4, where we demonstrate the implementation of our modeling and control framework and evaluate the economic and energy impact of our developments. Finally, we draw a series of conclusions in Section 5.

2. Background: optimal control strategies for buildings

Engaging HVAC systems in DR strategies involves operating the system at a higher level than actually needed during the off-peak hours, and storing the excess energy (heating or refrigeration) for use during peak times. Since storing energy incurs some losses, load leveling carries a penalty in terms of increased overall energy consumption. Incentives for implementing DR strategies are often provided in the form of time-of-use (TOU) pricing, where customers are subject to a time-sensitive rate structure similar to the market price for electricity, with energy prices typically much higher at peak times than in off-peak periods.

Shifting HVAC electricity demands in a TOU pricing framework calls for the use of an advanced control system, which, (i) can account for the dynamic prices and minimize operating costs through the use of TES, while, (ii) meeting indoor comfort requirements for the building occupants and, (iii) preserving the integrity of the equipment and abiding by all operating constraints. Initially developed for applications in the chemical industry, Model Predictive Control (MPC) provides an ideal framework for addressing these goals and has recently become of major interest in the buildings sector [9]. It consists of a dynamic optimization that is repeatedly solved over a finite, rolling time horizon [10] that yields trajectories of system inputs.

The development of such predictive control strategies for buildings is, however, a challenging task, owing to several (potentially conflicting) requirements. The controller, must (i) account for a long time horizon (at least equal to the period of time for which electricity price and weather predictions are available), but may, (ii) potentially be executed frequently, such that control decisions are made over an appropriate time scale to account for short-term fluctuations in, e.g., weather and occupancy. Moreover, (iii) the controller must include sufficient information about the building dynamics (i.e., incorporate an appropriate model), and (iv) set the operating mode (e.g., charge, discharge) of TES storage systems, which, in turn, involves making integer, rather than continuous, decisions.

Most industrial applications of MPC rely on a tracking objective function, formulated in terms of minimizing the discrepancy between a (subset) of the system states and their corresponding target values (setpoints). In the case of HVAC systems, rather than tracking a prescribed temperature setpoint, it is more advantageous to formulate the controller objective function to account directly for operating cost. In this case, the indoor temperature is allowed to vary within specified upper and lower comfort limits, and serves as an important handle for reshaping the energy consumption profile of the building. This approach is referred to as economic MPC (E-MPC), and it has been increasingly adopted in buildings energy management research and applications [5,11–13]. By accounting for the costs associated with dynamic changes in ambient conditions, occupancy and energy prices, E-MPC can outperform steady-state optimization and heuristics-based approaches from an economic perspective [14,15].

Using economic MPC for advanced energy management in buildings thus consists of solving an optimization problem repeatedly over a prediction time horizon T that is periodically shifted forward in time. The objective of the problem is formulated in terms of operating cost (based on energy consumption), and the optimal value is established subject to ($s.t.$) a set of constraints,