Model Predictive Control of Building On/Off HVAC Systems to Compensate Fluctuations in Solar Power Generation

Jin Dong*, Mohammed Olama†, Teja Kuruganti†, James Nutaro†,
Yaosuo Xue‡, Christopher Winstead† and Alexander Melin§
* Building Envelope & Urban Systems Research Group, Oak Ridge National Laboratory, Oak Ridge, TN 37831
dongj@ornl.gov
† Modeling and Simulation Group, Oak Ridge National Laboratory, Oak Ridge, TN 37831
{olamahussemm, kurugantipv, nutarojj, winsteadcj}@ornl.gov
‡ Power & Energy Systems Group, Oak Ridge National Laboratory, Oak Ridge, TN 37831
xuey@ornl.gov
§ Sensors & Embedded Systems Group, Oak Ridge National Laboratory, Oak Ridge, TN 37831
melina@ornl.gov

***Abstract*—The high variability in solar photovoltaic (PV) power production causes voltage variations temporally and spatially on distribution feeders and substations. To tackle this problem, we propose absorbing most of the PV power generation locally by building loads such as heating, ventilation and air conditioning (HVAC) units to minimize the impact on the grid and reduce the need for large energy storage devices. In this paper, we formulate a mixed integer quadratic optimization problem to optimally dispatch a fleet of on/off HVAC units to consume most of PV power generation locally while maintaining occupants comfort and hardware constraints. On/off HVAC units are widely available in residential buildings in addition to many small to medium size commercial buildings. Simulation results show that by assigning the proper number of aggregated HVAC units, the proposed mechanism achieves good PV tracking performance without jeopardizing occupants comfort. This study concludes that most of the PV generation can be consumed by building loads with the help of proper control strategies, thereby permitting to increase solar PV penetration levels.**

I. Introduction

The deployment of distributed energy resources (DERs) has increased dramatically over the last decade, especially solar photovoltaics (PV). Higher penetration of renewables, with their uncontrollable generation variability, imposes significant grid stability challenge [1]. An increase in solar PV penetration can create distribution voltage rise issues and reduce the lifetime of the distribution transformer due to frequent change in tap positions. Solar PV generation can assist in serving part of the local loads to potentially decrease the stress on the distribution feeder and improve overall system performance. However, PV panel power output can vary rapidly due to weather conditions, passing clouds or flocks of birds, and local intermittent shading. To deal with these issues, energy storage systems are required that impose significant storage capacity for evening and night loads. Storage devices are often discussed to capture uncertainty in electricity produced by solar PV. However, current electrical storage technologies require large capital investments, which is the motivation for pursuing research for other options such as the employment of building assets. In this way, buildings can consume the solar PV generation locally as much as possible and impose minimal impact on the grid and energy storage systems. Buildings account for 73% of total electricity consumption in the United States and therefore will play a crucial role in the future of the national electric power system. Total annual US energy consumptions are roughly equal for residential and commercial buildings with Heating, Ventilation and Air-Conditioning (HVAC) loads that account for about half of their energy use [2], [3]. This motivates research in developing control methods for using building HVAC loads to consume generated solar PV power locally and reduce the need for conventional electrical storage. Building thermal mass can be used for demand dispatch because it can significantly affect building thermal response and corresponding power consumption of HVAC system due to the considerable thermal capacities and resistances in it.

A significant body of research has grown out of the above literature in response to open challenges around aggregate model efficacy and efficiency, modeling and control framework. The use of building HVAC systems for providing demand side services was examined in [4]–[8]. In particular, the works in [7], [8] illustrate the potential promise of model predictive control (MPC) for energy efficiency in buildings. Researchers in [9] investigated the aggregation of thermo-

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statically controlled loads (TCLs) to simultaneously provide frequency and voltage regulation services, recognizing that solving these problems separately can produce suboptimal solutions. [10] presented a methodology to enumerate the flexibility of thermostatically controlled appliances.

Recent research on residential loads [11], [12] such as HVAC and refrigerators has shown that they can provide grid ancillary services with the help of appropriate control algorithms. One drawback of residential loads is that they are largely on/off control, which greatly reduces the flexibility of control strategies that can be applied. Such a drawback will be tackled in this paper by considering a coordination and control of a fleet of on/off loads to allow total consumption of PV power generation.

In this paper, a mixed integer quadratic optimization problem is formulated to optimally dispatch an aggregate of on/off HVAC units and allow total consumption of PV power generation while maintaining occupants comfort and hardware constraints. Simulation results show that the proposed mechanism is able to offset 85% more of local PV power than the traditional basic thermostat control.

The closest related prior work to the present paper is the centralized MPC design recently published in [13], [14], where an aggregate state-bin demand model is used to directly control the loads. Those works present solar mitigation schemes with a large temperature regulation band - note that the results shown in [13], [14] assume end-of-use temperature regulation bands four times wider than those typically used. In contrast, the present paper considers discrete controllers that are applicable to on/off HVAC systems that are available in residential buildings in addition to many small to medium size commercial buildings. Finally, a comparison with a traditional basic on/off control is presented in this study.

The remainder of this paper is organized as follows. Section II introduces the building thermal model of an on/off HVAC unit. Section III then derives an optimization formulation for aggregated HVAC loads. Section IV presents the simulation results to validate the tracking performance using a set of real temperature and solar PV power data. Finally, Section V summarizes the paper and presents the conclusions.

II. System Modeling

A. Building Thermal Model

In this section, we describe the typical one dimensional resistance-capacitance (RC) model used in this work and formulate the problem. The system model was widely utilized in the literature such as [11], [15]. Consider the following continuous-time linear time invariant (LTI) system based on the dynamics of the room temperature and outside air temperature:

$$\dot{T} = \frac{1}{RC}T_{out} - \frac{1}{RC}T + \frac{1}{C}Q_{out} + \frac{Mode_{HVAC}}{C}Q_{HVAC} \qquad (1)$$

where the system parameters used in the above model are defined in Table I, where the system state is the room air temperature T.

TABLE I: Building thermal model parameters definition

Variables	**Definition**
T_{out}	Outside air temperature [$°C$]
T	Indoor air temperature [$°C$]
C	Thermal capacity
R	Thermal resistance
$Mode_{HVAC}$	0: OFF; 1: ON
Q_{out}	Heat gain from solar irradiance
Q_{HVAC}	Cooling capacity of HVAC [kW]

If we denote state vector $X = [T]$, inputs $U = [Mode_{HVAC}]$, and disturbances $V = [T_{out}, Q_{out}]$, we can rewrite the building thermal model in (1) into the state-space form as:

$$\dot{X} = AX + BU + GV. \qquad (2)$$

It should be mentioned that we are doing summer cooling case with discrete ON/OFF control in this paper. State-space matrices A, B, G can be obtained for any given building, and disturbance V is recorded for that specific location.

B. Baseline Control Strategy

The performance of the proposed adaptive control scheme will be compared with a baseline basic on/off control scheme commonly used by thermostats in residential homes. The essential behavior of mechanical and digital controls of thermostats in residential homes can be modeled with four rules. These rules monitor the air temperature T and compare it to a reference temperature T_{ref} that is offset by a cooling dead band ΔT_c and heating dead band ΔT_h. On the basis of this comparison, the air conditioning unit is turned off, set to heat, or set to cool as follows:

1) If $T \geq T_{ref} + \Delta T_c$, then cool;
2) If $T \leq T_{ref} - \Delta T_h$, then heat;
3) If cooling and $T \leq T_{ref}$, then off;
4) If heating and $T \geq T_{ref}$, then off.

This control strategy keeps the temperature between $T_{ref} - \Delta T_h$ and $T_{ref} + \Delta T_c$. In practice the dead bands must be large enough, or an explicit delay must be introduced, to avoid rapid cycling of the air conditioning units (e.g., to ensure at least 10 minutes between mode changes). This simple control approach does not consider effects such as local weather, building uses, individual unit energy consumption, and total building energy consumption.

In the sequel, we will investigate whether it is possible to locally consume the PV generation by aggregating HVAC loads only. More importantly, an optimal scheduling framework is proposed to dispatch HVAC loads without jeopardizing occupants' comfort.

III. Optimization Problem Formulation

In the summer cooling scenario with ON/OFF discrete control, the thermostat setting point we choose is $23°C$. And a $\pm 0.5°C$ comfort band is allowed. This section develops a centralized MPC control strategy to absorb fluctuations in solar power generation by directly controlling the aggregate demand of on/off HVAC systems.

We consider the problem where indoor temperature $x = T$ is required to remain within certain bounds of a constant dead-band in the presence of the disturbance vector V. Moreover, we make the indoor temperature x_j (j corresponds to j_{th} building) track a pre-assigned reference temperature set-points T_{ref} by minimizing the state error $\varepsilon_j(k) := x_j(k) - T_{ref}$ at each time step k, where T_{ref} is the temperature set-point of x.

MPC is implemented as a sampled-data controller using the continuous building thermal model discretized with sampling period $\triangle T = 10$ minute, $t_i = i\Delta T$ which yield the discrete-time model

$$x_{k+1} = A_k x_k + B_k u_k + G_k v_k. \quad (3)$$

Our main objective is to design optimal control signals to make the aggregate demand of HVAC systems follow PV power generation without violating temperature comfort requirement.

$$z(k) := \sum_{j=1}^{N_s} u_j(k) \approx P_{PV}(k), \quad (4)$$

where N_s denotes total number of HVAC units, and $u_j(k)$ means control action taken for j_{th} building at k_{th} time interval.

A. Cost Functions

The overall cost function of this optimal coordination problem can be listed as:

$$J = \sum_{k=1}^{N_p} \Big\{ (z(k) - QP_{PV}(k))^2 + (\sum_{i=1}^{N_s} R\varepsilon_i(k)^2) \Big\}, \quad (5)$$

where N_p represents the prediction horizon with Q and R being weighting factors.

B. Constraints

We have both states and control inputs constraints in this problem. For temperature state constraint, we set $x \in [22.5°C, 23.5°C]$. Then for the discrete ON/OFF control signal, it is forced to be binary inputs $u \in \{0, 1\}$. Notice here, 0 means HVAC OFF, and 1 means HVAC ON. In contrast to traditional continuous decision problem, this formulation turns out to be a mixed integer quadratic programming problem which can be readily solved by commercial solver.

IV. Case Studies

This section presents a numerical example to validate our proposed optimal building load control, which outperforms the baseline control. We consider a central coordinator that collects total PV generation, and allocates energy to a group of HVAC loads to minimize difference between total power consumption and PV generation.

In both basic control and MPC simulations, we utilize 100 buildings, each of which is equipped with identical RC model. It is worth mentioning that terminal simulation time is $N = 432$, which means 10 mins per time step for three days. Both PV generation and weather profiles are picked for the same day from a local station. All numerical simulations are coded in MATLAB and solved using Gurobi [16] through the YALMIP interface [17]. It should be mentioned that, ΔT_h and ΔT_c are chosen to be 0.5°C in the basic control with reference temperature set to be 23°C. While the comfort band for adaptive optimal control is $[22.5°C, 23.5°C]$.

All the simulation results are illustrated in Figs. 1 - 9.

A. Tracking Performance

The simulation results for indoor temperatures and control signals of all 100 buildings are shown in Figs. 1 - 4 for basic control and MPC, respectively. While a detailed comparison of the temperature for a randomly picked building (which is 18) is illustrated in Fig. 5. Observing the temperature comparison in Figs. 1, 2 and 5, the indoor temperatures maintain closely inside the desired comfort band. However, we do notice the indoor temperatures are better regulated (never cross out of comfort band) using MPC. Figs. 3 and 4 clearly show the designed discrete on/off control signals under those two different control strategies.

Recall the objective of this paper is to track the PV generation without deviating indoor temperature out of a bound. After checking the temperatures in bound, we need to evaluate the tracking performance depicted in Fig. 6 - 7. It can be seen from Fig. 7 that satisfied tracking performance has been achieved, even with the presence of highly dynamic solar PV generation during the noon. It should be mentioned that although Fig. 6 shows some rough consistence between the power consumption and PV generation, it is not considered to be any tracking regulation. A reasonable explanation for this observation is the time consistence between maximum PV generation and peak temperature during a day that leads to peak cooling demand for the HVAC system. In contrast, in Fig. 7, we see 100 HVAC loads are well coordinated to track the PV generation using the proposed adaptive optimal control. Moreover, a focused view of 1 day tracking performance is plotted in Figs. 8 and 9, that can successfully minimize this confusion.

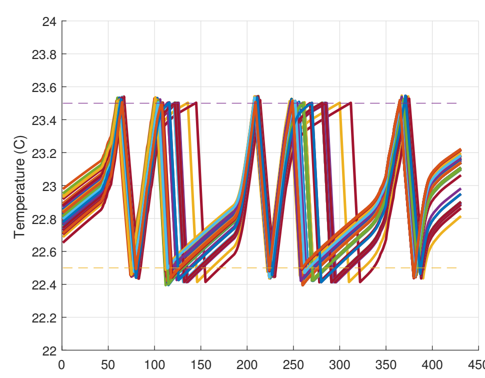

Fig. 1: Indoor temperature for 100 buildings under basic control

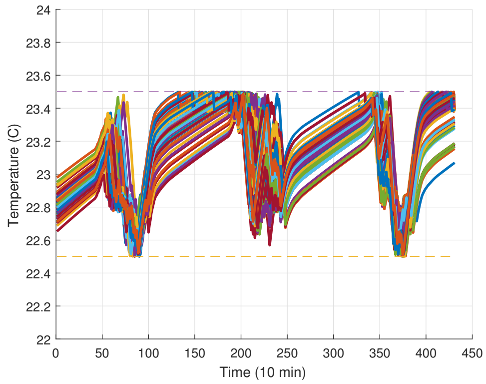

Fig. 2: Indoor temperature for 100 buildings under MPC

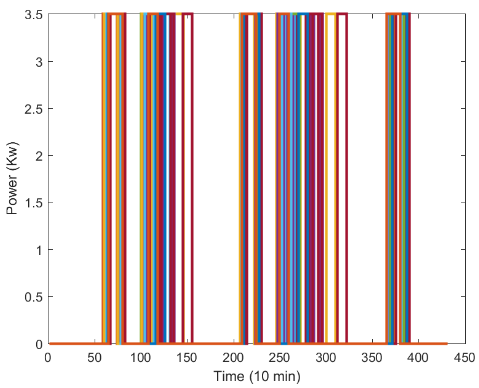

Fig. 3: Basic control signals

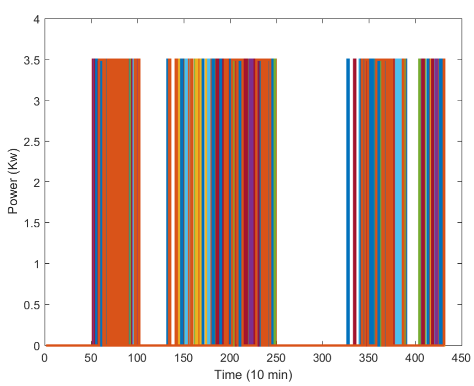

Fig. 4: MPC control signals

B. Performance Metric

We use the Root Mean Squared Error (RMSE) to characterize the tracking error, which is denoted by the following equation.

$$MSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(z(k) - P_{pv}(k)\right)^2}, \tag{6}$$

where, $z(k)$ is defined in (4).

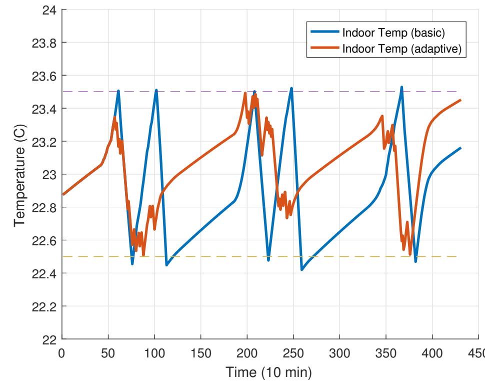

Fig. 5: Temperature comparison for Building 18

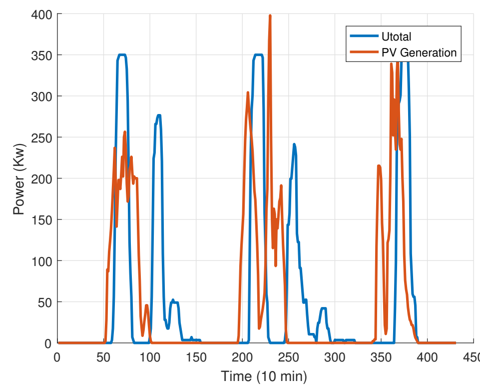

Fig. 6: Tracking under basic control

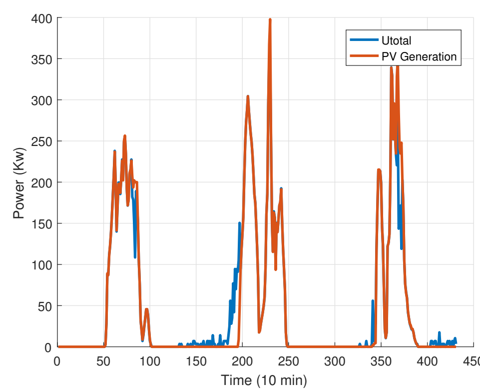

Fig. 7: Tracking under MPC control

Through Table II, we see that the proposed MPC strategy absorbs 85% more local PV generation than the basic control strategy.

V. CONCLUSIONS

We have developed optimal coordination of HVAC loads to directly emulate an energy storage device, that is, to mitigate fluctuations in PV generation. We consider on/off HVAC units

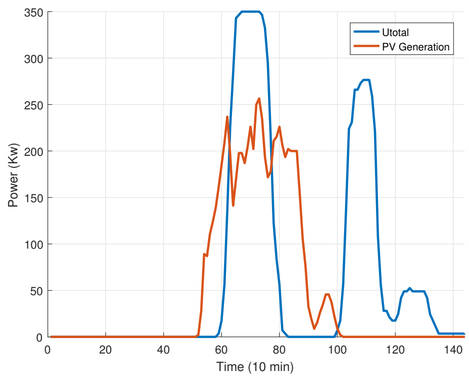

Fig. 8: Detailed view of 1 day tracking under basic control

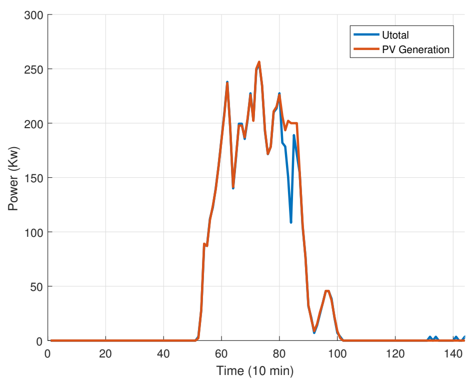

Fig. 9: Detailed view of 1 day tracking under MPC control

which are available in residential buildings in addition to many small to medium size commercial buildings. A mixed integer quadratic optimization problem is formulated to optimally dispatch an aggregate of on/off HVAC units to consume most of PV power generation locally while maintaining occupants comfort and hardware constraints. Simulation results show that the proposed mechanism is able to achieve good PV tracking performance while employing a proper number of aggregated HVAC units. This study concludes that most of the PV generation can be consumed by building loads with the help of proper control strategies, thereby permitting to increase solar PV penetration levels. For the future work, we will work on a decentralized/distributed version of this work for large scale aggregation.

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TABLE II: Performance Metric for Comparison

Control Strategy	**Tracking RMSE**
Basic Control	113.17
MPC	18.74

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