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Model predictive control for building loads connected with a residential distribution grid

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HIGHLIGHTS

- Development of a Model Predictive Control (MPC) for residential buildings connected with grid.
- Optimization on 15,000 residential building energy devices with a 342-node IEEE distribution grid.
- Findings show 21% generation cost reduction and a 17% peak load reduction.

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ABSTRACT

Aggregated control of electrical loads in a large cluster of buildings has been a challenge due to the complexity of the system involving generators, grid constraints, load serving entities complex load models, and people behavior. This paper introduces a novel load aggregation method in an electricity distribution system with Model Predictive Controlled (MPC) loads. This method closes the control loop from power generation to people behavior, resulting in a more stable and efficient integrated buildings-to-grid system. A behavior-driven price-based MPC is introduced for a residential building energy management system, which controls the air conditioner (AC), electric vehicle (EV), water heater, and battery energy storage system. A nodal pricing method is introduced representing power generation and distribution costs, which is mathematically proven to stabilize the system with MPC controlled loads. The method is tested in a 342-node residential building distribution network with 15,000 buildings which is inverse sampled from hundreds of actual smart meter data. The results show a 21% reduction in generation cost, 17% reduction in peak load, and reduced nodal voltage drop from the coordinated control system.

1. Introduction

The current electricity grids are over-dimensioned to meet the high peak demand in extreme consumption periods. About 20% of the current electricity grid generation capacity is built to meet the peak demand that occurs only 5% of the times [1]. Beside the requirement of adding more infrastructure to meet this peak demand, this period is associated with high generation and transmission costs. Currently, the generation and transmission of electricity is controlled to meet the demand at all times, which is unsustainable and hardly affordable [2]. A sustainable and more reliable solution would be involving electricity consumers in the grid operation. Among these consumers, buildings stand for about 70% of electricity consumption and the residential sector stands for 36% of electricity consumption in the United States [3]. In an attempt to involve these sectors in the grid operations, different retail pricings and demand response programs are deployed, such as time-of-use (TOU) tariff, critical-peak pricing (CPP), and inclining block rate (IBR). However, they are far from the real-time cost of electricity determined in day ahead and real-time markets. These demand response programs reflect an average of daily price changes or they consider a few instances a year to reflect high peak prices [4]. This is due to the fact that, current buildings' operations hardly consider grid requirements in its consumption. The buildings and people as end users consume electricity at any time without cost considerations. The main challenge in involving buildings in the real-time market is the lack of an automated control system in this sector, which is able to participate in this market while maintaining people's satisfaction. People's satisfaction is an important part of a buildings-to-grid integration because most of the electricity consumptions are associated with people activities in buildings, including appliances usage, illumination, and thermal comfort. People activities and comfort are mainly responsible for peak consumptions in hot summer days, extremely cold winter days, after

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Nomenclature

A_j, B_j	system j linear dynamics
A_j^{AC}, B_j^{AC}	building thermal linear dynamics
a_p, b_p, c_p	polynomial supply curve function gains
a_j^{AC}, b_j^{AC}, c_j^{AC}, d_j^{AC}, e_j^{AC}, f_j^{AC}	AC maximum thermal capacity curve coefficients
$A_V^{k_G \times k_G}$	node voltage drop sensitivity matrix
β_j^i	status of the device j at step i (ON = 1, OFF = 0)
B	imaginary element of the network admittance matrix
B_{kn}	(k_{th}, n_{th}) imaginary element of the network admittance matrix
C_w	water specific heat
COP_j^i	AC coefficient of performance
$C_V^{k_G \times m_G}$	node voltage drop cost
dt	time step
$f(x)$	supply price function
$g_1(x)$	function calculating substation load (power flow calculations for load)
$g_2(x)$	function calculating voltage at each node (power flow calculations for voltages)
G	real element of the network admittance matrix
G_{kn}	(k_{th}, n_{th}) real element of the network admittance matrix
$h_j(x)$	power consumption function for device j
i	time step starting at current time
j	consumer index
J_{AC}	set of indices associated with AC units
J_{Bat}	set of indices associated with batteries
J_{EV}	set of indices associated with EVs
J_{WH}	set of indices associated with water heaters
$\mathscr{j}$	imaginary unit
θ_k^i	voltage angle at bus k of the distribution grid at step i
K_V	voltage drop cost gain
K_{j_wh}	water heater tank thermal conductivity
LB_j^{i+1} UB_j^{i+1}	system states: upper and lower bound functions
M_j	water heater j storage tank capacity
$\dot{m}_j^i$	hot water use rate at step i for water heater j
m_j	prediction horizon for device j
m_G	aggregated prediction horizon
N_G	total number of nodes in the distribution system
N_j	number of MPC controlled consumers
$\mathbb{N}_k$	set of consumers at node k of the distribution system
η_j^c	EV j charging performance gain
η_j^d	EV j discharging performance gain
η_j^C	PV battery charging performance
η_j^D	PV battery discharging performance
η_j^I	inverter performance gain
η_j^R	rectifier performance coefficient
π_j^{i+1}	behavior based probabilities
$P_{j\_WHelement}$	water heater j heating element power
P_j^{i-d}	EV j discharging power
Pin_j^i	PV battery input power
$Pout_j^i$	PV battery output power
Pg_j^i	building total load on the distribution grid
Pl_j^i	building total load without PV and battery
Pr_j^i	rectifier power input
Pi_j^i	inverter output power
Ppv_j^i	generated solar power
P_j^i	power consumption or generation for consumer j at step i
Pb_k^i	real load on the bus k of the distribution grid at step i
PF_j	device j power factor
ρ_{Gen}^i	generation price
ρ_j^i	electricity price for consumer j at step i
$\rho_V^{k_G \times m_G}$	voltage drop penalty price at each node for grid prediction horizon steps
Qb_k^i	reactive load on the bus k of the distribution grid at step i
Qac_j^i	thermal heat input from AC at step i to building j
$Qcap_j^i$	AC in building j at step time i maximum thermal capacity
Qi_j^i	internal heat gain for building j at step i
Qs_j^i	solar input heat to building j at step i
Q_{j_ev}	EV j battery capacity
Q_{j_b}	PV battery capacity
r_l	Resistance of line l
Sb_0^i	apparent power at substation level at step i
S_j^i	consumer j apparent power at step i
s_j^i	free variable for constraint relaxation
$SOC_{j\_ev}^i$	EV j battery state of charge at step i
t_i	current time
t_{i+PH}	time at the end of prediction horizon
t_{i+CH}	time at the end of control horizon
T_a	water heater ambient temperature
T_{Ground}^i	ground temperature
$T_{j\_in}^i$	indoor air temperature
$T_{j\_wh}^i$	hot water temperature
T_{out}^i	outdoor temperature
$\mathbb{U}_j$	system j feasible control actions
U_j^i	system j control action at step i
V_k^i	voltage at bus k of the distribution grid at step i
$V^{k_G \times m_G}$	nodal voltages matrix at all time steps and location
x_l	line l reactance
X_j^i	system j states at step i
Y	network admittance matrix
Y_{kn}	(k_{th}, n_{th}) element of the network admittance matrix
ω_j	penalty weights for constraint relaxation for consumer j
z_l	line l impedance

work hours during work days, and shifted peak consumption on weekends [5]. To effectively shift these peak loads, one should consider people behavior and satisfaction models in its controller design [6]. This study introduces a building-to-grid integration method for residential buildings, which connects people behavior with building operation and the grid requirements.

1.1. Prior studies

Different control methods can be used to manage building load considering real time price and occupancy satisfaction. Model Predictive Control (MPC) has been the subject of many studies due to its capabilities of combining operation costs as a minimization objective and users' satisfaction as a constraint. This controller can be used in most in-building energy consumer devices, such as heating, ventilation, and air conditioning (HVAC) system, electric vehicle (EV), water heater, washing machine, pool pump, and schedulable appliances. The MPC is widely studied to utilize thermal energy storages, such as water heater, air conditioner (AC), and refrigerators, to shift energy consumption [7]. This capability can be utilized for demand response programs, TOU electricity rates, and ancillary services [8,9]. The HVAC MPC problem is associated with occupancy behavior and modeling, in which people's presence and comfort can greatly affect the HVAC energy savings [10,11]. In an effort of considering people behavior and satisfaction in HVAC operations, several methods have been used along with MPC, including Markov chain for occupancy predictions and PMV