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Flexibility assessment of grid-interactive commercial buildings considering multi-zone thermal coupling



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Abstract: Commercial buildings, characterized by substantial cooling loads and thermal inertia, serve as vital flexible resources for low-carbon power systems. However, existing approaches often fail to capture thermo-electric coupling under multi-zone thermal interactions and neglect user-side efficiency, which necessitates a more robust flexibility assessment framework. This paper proposes a thermo-electro-efficiency coupled framework to evaluate the summer demand response of grid-interactive commercial buildings. We develop a multi-zone third-order RC model with explicit inter-zone and public-area heat transfer, which is combined with a building-level HVAC model to correlate available cooling capacity, part-load ratio, and variable COP. Implementation of this strategy during demand response events yields significant efficiency gains. Specifically, it achieves a 4.6% higher COP retention than an aggressive rule-based baseline, with strict adherence to indoor thermal comfort limits. Furthermore, sensitivity and Pareto analyses delineate efficiency-oriented, balanced, and deep-response operating regimes. These insights provide a practical foundation for flexibility evaluation and pre-event strategy formulation.

Keywords: flexibility assessment; demand response; virtual energy storage; multi-zone thermal model; non-constant COP

1. Introduction

Carbon-neutrality targets and high renewable penetration necessitate demand-side flexibility for secure grid operation [1,2]. Commercial air-conditioning systems emerge as prime candidates for grid-interactive demand response, given their substantial power ratings, precise controllability, and short-term thermal storage capacity. Large-scale assessments confirm that building flexibility and efficiency drastically reduce power-system costs and emissions. Concurrently, climate-driven surges in weather-sensitive thermal demands require high-resolution temporal representations [3]. These challenges intensify at the cluster scale, where structural and operational barriers restrict the practical deployment of flexibility [4].



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While commercial building clusters provide vast aggregate capacity for short-term operational flexibility, their diverse thermal states and equipment conditions obscure actual flexibility characterization. A cluster's practical demand response relies heavily on explicit inter-zone heat transfer, dynamic load redistribution, and user-side efficiency degradation. Such multi-physics interactions invalidate simple load-reduction metrics. This underlying complexity demands a coordinated framework to map the explicit boundaries among power response, efficiency penalties, and thermal comfort.

Existing studies can be broadly divided into two groups. The first group concentrates on building-grid interaction and control-oriented DR strategies. Recent studies have proposed transactive control architectures for commercial HVAC systems to support multiple grid services [5], demonstrated the value of model predictive control for commercial HVAC flexibility in both simulations and field applications [6], and investigated thermal-storage-assisted MPC for commercial buildings participating in DR programs [7]. Learning-based strategies have also been developed for multi-thermal-zone demand response and energy management [8]. In parallel, empirical or device-oriented studies have examined cooling setpoint adjustment in commercial buildings [9] and assessed commercial-building flexibility using advanced rooftop-unit models that explicitly evaluate comfort impacts in cooling season [10]. These studies demonstrate that commercial buildings can provide useful DR services, but they mainly focus on control performance or specific implementation pathways.

The second group concentrates on flexibility characterization and thermal representation. A generic bottom-up method for quantifying building energy flexibility was introduced in [11], while building thermal mass clustering was further used in [12] to classify buildings according to their dynamic flexibility potential. Experimental studies have investigated the DR potential of passive thermal mass combined with active storage [13], quantified the thermal inertia of commercial buildings under thermostat excitation tests [14], and proposed quantitative DR performance metrics that explicitly consider rebound effects and parameter influences [15]. These studies improve the understanding of building flexibility, but they usually emphasize either thermal flexibility characterization or DR performance quantification, rather than the full thermo-electric-efficiency interaction at the commercial-building-cluster level.

Despite this progress, two key gaps remain. First, many existing studies still rely on single-zone or strongly aggregated thermal representations, which are insufficient to capture room-to-room heat transfer and the role of corridors or public areas in redistributing thermal flexibility within a building cluster. Second, user-side efficiency is often oversimplified through constant-COP assumptions or static power mappings. Consequently, the coupled effects of available cooling capacity, part-load ratio, non-constant COP, and HVAC dynamics on practical response capability are not adequately captured. These two gaps directly limit the credibility of virtual energy storage assessment for commercial building clusters.

To address these issues, this paper develops a thermo-electro-efficiency coupled modeling and evaluation framework for commercial building clusters under summer cooling conditions. Instead of representing flexibility by a single reduction value, the proposed framework characterizes it through a coordinated response-efficiency-comfort boundary. The main contributions are as follows:

- (1) A cluster-level multi-zone thermal framework is established using third-order RC dynamics with explicit room-to-room and room-to-public-area coupling, so that the spatial redistribution of thermal flexibility can be represented more realistically.

(2) A building-level thermo-electric HVAC model is developed by connecting available cooling capacity, part-load ratio, non-constant COP, and first-order equipment dynamics, thereby capturing operating-point migration and efficiency changes during demand response.

(3) A thermo-electro-efficiency coupled response evaluation method is proposed to compare conservative, edge-approaching, and aggressive DR strategies and to identify efficiency-oriented, balanced, and deep-response operating conditions through scenario analysis, sensitivity analysis, and Pareto-based screening.

The remainder of this paper is organized as follows. Section II presents the thermo-electro-efficiency coupled modeling framework, including the multi-zone thermal model, the building-level HVAC response model, and the evaluation metrics. Section III reports the case-study results, including scenario comparison and parametric trade-off analysis. Section IV concludes the paper.

2. Methods

2.1. Multi-zone third-order RC thermal model

For zone in i building b , three thermal states are considered: indoor air temperature $T_{a,b,i}$, internal mass temperature $T_{m,b,i}$, and envelope equivalent temperature $T_{e,b,i}$. The third-order RC thermal model is formulated as

$$C_{b,i}^a \dot{T}_{a,b,i} = \frac{T_{m,b,i} - T_{a,b,i}}{R_{b,i}^{am}} + \sum_{j \in N_i^{room}} \frac{T_{a,b,j} - T_{a,b,i}}{R_{b,ij}^{adj}} + \sum_{k \in N_i^{pub}} \frac{T_k - T_{a,b,i}}{R_{b,ik}^{pub}} + Q_{b,i}^{int} - Q_{b,i}^{hvac}, \quad (1)$$

$$C_{b,i}^m \dot{T}_{m,b,i} = \frac{T_{a,b,i} - T_{m,b,i}}{R_{b,i}^{am}} + \frac{T_{e,b,i} - T_{m,b,i}}{R_{b,i}^{me}}, \quad (2)$$

$$C_{b,i}^e \dot{T}_{e,b,i} = \frac{T_{m,b,i} - T_{e,b,i}}{R_{b,i}^{me}} + \frac{T^{out} - T_{e,b,i}}{R_{b,i}^{eo}} + \alpha_{b,i} I_{sol,o(i)}. \quad (3)$$

where $C_{b,i}^a$, $C_{b,i}^m$, and $C_{b,i}^e$ are equivalent thermal capacitances, and $R_{b,i}^{am}$, $R_{b,i}^{me}$, and $R_{b,i}^{eo}$ are thermal resistances. The set N_i represents adjacent rooms, while P_i represents corridors or public areas coupled with zone i . $Q_{b,i}^{int}$, $Q_{b,i}^{sol}$, and $Q_{b,i}^{hvac}$ denote internal heat gain, solar heat gain, and HVAC cooling delivered to the zone, respectively. The main parameters of the model are summarized in Table 1.

Table 1. Parameters for zone thermal model generation.

Parameter	Value	Description
$C_{b,i}^a$	0.03–0.05 kWh/m ² K	18Air capacitance
$C_{b,i}^m$	0.22–0.42 kWh/m ² K	Internal-mass capacitance
$C_{b,i}^e$	0.35–0.60 kWh/m ² K	Envelope capacitance
$R_{b,i}^{am}$	1.6–2.9 °C/kW	Air-to-internal-mass resistance, perimeter zones
$R_{b,i}^{me}$	2.5–5.0 °C/kW	Internal-mass-to-envelope resistance, perimeter zones
$R_{b,i}^{eo}$	2.0–4.8 °C/kW	Envelope-to-outdoor resistance, perimeter zones

The inter-zone coupling terms in (1) are important because local cooling reduction during DR can affect neighboring zones through heat transfer. Therefore, the flexibility of grid-interactive commercial buildings cannot be fully represented by independent single-zone models.

2.2. Thermo-electric HVAC response model

To bridge the building's thermal dynamics with equipment operational limits, the zone-level cooling command is determined according to the zone temperature, thermal mass temperature, outdoor disturbance, internal heat gain, solar gain, comfort target, and scenario-dependent control weights. The zone-level commands are aggregated to the building level as:

$$Q_b^{cmd}(k) = \sum_{i \in Z_b} Q_{b,i}^{cmd}(k), \quad (4)$$

where Z_b is the set of zones in building b . It should be noted that $Q_b^{cmd}(k)$ is a cooling command rather than the actual delivered cooling. The actual cooling output is limited by equipment dynamics and available cooling capacity.

The available cooling capacity is modeled as a function of equivalent evaporating and condensing temperatures:

$$Q_b^{avail}(k) = Q_b^{rated} \phi_b^{cap}(T_b^{eva}(k), T_b^{cond}(k)), \quad (5)$$

where Q_b^{rated} is the rated cooling capacity and ϕ_b^{cap} is a temperature-dependent capacity correction function. The equivalent condensing temperature is calculated as:

$$T_b^{cond}(k) = T^{out}(k) + \Delta T_b^{cond, app} + \gamma_b^{cond} \frac{Q_b^{cool}(k)}{Q_b^{rated}}, \quad (6)$$

and the equivalent evaporating temperature is calculated as:

$$T_b^{eva}(k) = T_b^{rep}(k) - \Delta T_b^{eva, off} - \gamma_b^{eva} \frac{Q_b^{cool}(k)}{Q_b^{rated}}, \quad (7)$$

where $T_b^{rep}(k)$ is the representative building temperature. It can be evaluated using an area-weighted average, hot-zone-biased average, or a hybrid representative temperature depending on building characteristics.

To accurately reflect equipment performance degradation under varying conditions, the PLR is then defined by the ratio of actual cooling output to available cooling capacity, rather than utilizing a constant rated capacity.

$$PLR_b(k) = \frac{Q_b^{cool}(k)}{Q_b^{avail}(k)}. \quad (8)$$

Under high outdoor temperature or unfavorable equipment conditions, $Q_b^{avail}(k)$ decreases, which increases the effective PLR even if the actual cooling output remains unchanged.

The COP of building b is modeled as:

$$COP_b(k) = COP_b^{rated} \cdot \phi_b^{plr}(PLR_b(k)) \cdot \phi_b^{temp}(T_b^{eva}(k), T_b^{cond}(k)), \quad (9)$$

$$\phi_b^{plr}(PLR_b(k)) = a_0 + a_1 \cdot PLR_b(k) + a_2 \cdot PLR_b(k)^2 + a_3 \cdot PLR_b(k)^3, \quad (10)$$

$$\phi_b^{temp}(T_b^{eva}, T_b^{cond}) = b_0 + b_1 \cdot T_b^{eva} + b_2 \cdot (T_b^{eva})^2 + b_3 \cdot T_b^{cond} + b_4 \cdot (T_b^{cond})^2. \quad (11)$$

where COP_b^{rated} is the rated COP, ϕ_b^{plr} represents the part-load efficiency correction, and ϕ_b^{temp} represents the temperature-condition correction. The part-load correction is designed such that COP is highest near the optimal PLR and decreases under both low-load and high-load operation. This captures the fact that DR may change the equipment operating point and thus affect user-side efficiency.

The building electric power is calculated as:

$$P_b(k) = \frac{Q_b^{cool}(k)}{COP_b(k)} + a_b Q_b^{cool}(k) + b_b, \quad (12)$$

where $a_b Q_b^{cool}(k) + b_b$ approximates fan and pump auxiliary power. The aggregate HVAC electric power of the cluster is

$$P^{agg}(k) = \sum_b P_b(k). \quad (13)$$

The actual delivered cooling follows a first-order dynamic response:

$$Q_b^{cool}(k+1) = Q_b^{cool}(k) + \frac{\Delta t}{\tau_b} (Q_b^{cmd}(k) - Q_b^{cool}(k)), \quad (14)$$

subject to

$$0 \leq Q_b^{cool}(k) \leq Q_b^{avail}(k), \quad (15)$$

$$|Q_b^{cool}(k+1) - Q_b^{cool}(k)| \leq \Delta Q_b^{ramp}. \quad (16)$$

These constraints prevent unrealistic instantaneous changes in building power and make the simulated response more consistent with real HVAC operation.

2.3. Demand response scenarios and evaluation metrics

Four scenarios are considered. The baseline scenario represents comfort-priority reference operation without intentional demand response. The conservative DR scenario applies moderate pre-cooling, limited comfort-boundary utilization, and smooth recovery, so that user-side efficiency can be better preserved. The edge-approaching DR scenario reduces the pre-cooling margin and allows deeper use of the comfort boundary to achieve stronger average reduction. The aggressive DR scenario is used as a comparison case with deeper and coarser response actions and weaker efficiency protection.

The main performance metrics include:

$$\Delta P^{mean} = \bar{P}_{DR}^{base} - \bar{P}_{DR}^{mode}, \quad (17)$$

$$E^{red} = \sum_{k \in \mathbb{H}_{DR}} (P^{base}(k) - P^{mode}(k)) \Delta t, \quad (18)$$

$$\eta^{COP} = \frac{\overline{COP}_{DR}^{mode}}{\overline{COP}_{DR}^{base}}, \quad (19)$$

$$T_{zone}^{max} = \max_{b,i,k \in \mathbb{H}_{DR}} T_{a,b,i}(k) \quad (20)$$

where ΔP^{mean} is the average reduction, E^{red} is the reduction energy, η^{COP} is the COP retention ratio, and T_{zone}^{max} is the maximum zone temperature during the DR window.

2.4. Simulation-based response solving procedure

The results are obtained using a simulation-based response solving procedure rather than a strict optimization solver. At each time step, the algorithm updates zone thermal states, calculates cooling commands, estimates available cooling capacity and COP, applies equipment dynamics and ramp limits, and computes aggregate power. The procedure is repeated for all scenarios and sensitivity parameter combinations.

Algorithm 1: Thermo-electro-efficiency response solving

Input: $P_{bld}, P_{hvac}, P_{ctrl}, D_{ext}, [T_{start}, T_{end}], \Delta t$
Initialization: $k \leftarrow 0; x_b(0); Q_b^{cool}(0); P_b(0)$

- 1 **repeat**
- 2 Update $t_k, T^{out}(k), I_{sol}(k)$, and $Q^{int}(k)$
- 3 Compute zone cooling commands and aggregate $Q_b^{cmd}(k)$ using (4)
- 4 Estimate $T_b^{cond}(k), T_b^{eva}(k)$, and $Q_b^{avail}(k)$ using (5)–(7)
- 5 Compute $PLR_b(k)$ and $COP_b(k)$ using (8) and (9)
- 6 Update $Q_b^{cool}(k+1)$ using (12)–(14)
- 7 Compute $P_b(k)$ and $P^{agg}(k)$ using (10) and (11)
- 8 Solve (1)–(3), update $x_b(k+1)$, and evaluate metrics using (15)–(18)
- 9 $k \leftarrow k+1$
- 10 **until** $t_k \geq T_{end}$

3. Results

3.1. Commercial building cluster description

The studied case consists of eight commercial buildings, including office, retail, hotel, and mixed-use buildings. The total floor area is approximately 208,000 m², corresponding to a megawatt-scale aggregate HVAC load.

Four operating scenarios are examined: baseline operation, efficiency-aware conservative DR, edge-approaching DR, and aggressive DR. The baseline case represents comfort-priority operation without intentional DR, while the other three scenarios correspond to different levels of comfort-boundary utilization and efficiency protection during the demand response window from approximately 14:00 to 16:00. The main parameters of the case are summarized in Table II.

Table 2. Main parameters of the commercial building case.

Type	Area/m ²	Zones	Rated Cooling/kW	Rated COP	Optimal PLR
office	22000	18	1642.85	5.024	0.709
	26000	20	1872.78	5.201	0.605
	28000	20	1957.78	5.286	0.683
	32000	28	2319.62	5.098	0.662
retail	30000	26	2064.82	5.337	0.674
	24000	22	1576.05	5.32	0.652
	21000	20	1553.48	5.347	0.695
hotel	25000	22	1875.53	5.049	0.696

3.2. Aggregate response, COP, and thermal comfort comparison

Figure 1 presents a unified comparison of the four scenarios using three subplots: aggregate HVAC electric power, average COP, and maximum zone temperature. Because HVAC dynamics and smooth control transitions are explicitly considered, the power trajectories evolve continuously rather than exhibiting unrealistic step changes. The baseline case maintains the highest power level during the DR window, whereas the three DR scenarios achieve different degrees of reduction through different uses of thermal comfort margin.

The quantitative results are summarized in Table III. The average aggregate power during the DR window is 1.769 MW for baseline operation. It decreases to 1.371 MW in the conservative DR scenario, 1.041 MW in the edge-approaching DR scenario, and 1.063 MW in the aggressive DR scenario. The corresponding reduction energy values are 0.798 MWh, 1.457 MWh, and 1.412 MWh, respectively. These results indicate that the building cluster can provide significant demand reduction while maintaining a megawatt-scale operating level.

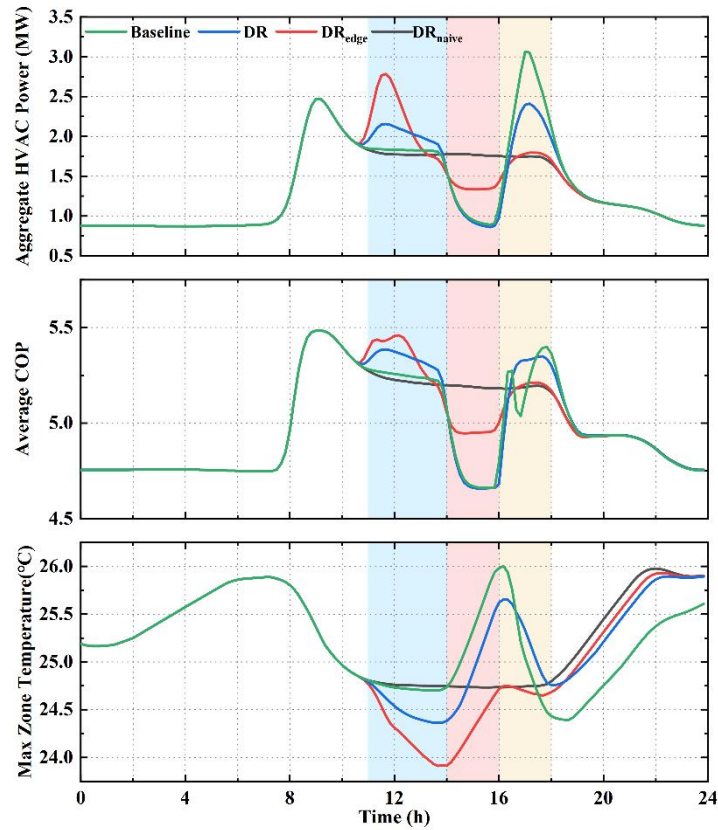


Figure 1. Aggregate HVAC power, average COP, and maximum zone temperature under four operating scenarios.

Table 3. Core results of the four operating scenarios.

Scenario	Baseline	DR	DR _{edge}	DR _{naive}
DR Window Mean/MW	1.769	1.371	1.041	1.063
DR Window Min MW	1.758	1.334	0.861	0.891
Avg Cop	5.191	4.964	4.738	4.747
COP Retention vs Base	1	0.956	0.913	0.914
Max Temp/°C	24.746	24.653	25.529	25.938
Reduction Energy/MWh	0	0.798	1.457	1.412

It is worth noting that the daily peak power values of different scenarios may remain close because the absolute peak can occur outside the DR window. Therefore, the DR-window average power and reduction energy are more representative indicators than the daily peak alone. In addition, the average COP during the DR window decreases from 5.191 in the baseline case to 4.964, 4.738, and 4.747 in the conservative, edge-approaching, and aggressive DR cases, respectively. The COP retention ratio decreases from 1.000 to 0.956, 0.913, and 0.914. Specifically, COP retention is measured as the fraction of baseline average COP maintained under each DR strategy. The aggressive rule-based strategy retains 91.4% of the baseline COP, while the proposed conservative strategy retains 95.6%. Therefore, the proposed method achieves a 4.6% higher COP-retention level, indicating better preservation of user-side cooling efficiency during DR operation. Meanwhile, the maximum zone temperature increases from 24.653 °C in the conservative DR case to 25.529 °C and 25.938 °C in the edge-approaching and aggressive DR cases. These

results indicate that deeper response is obtained through greater use of thermal comfort margin, while the proposed efficiency-aware strategy retains better cooling efficiency than the aggressive rule-based strategy.

3.3. Parametric trade-off analysis

Sensitivity analysis is conducted for the edge-approaching DR scenario by varying three parameters: pre-cooling intensity scale pre_{scale} , aggressiveness scale DR_{scale} , and HVAC dynamic time-constant scale τ_{scale} .

Figure 2 shows two-dimensional response surfaces at $\tau_{scale} = 1.0$. The horizontal axis is DR_{scale} , and the vertical axis is pre_{scale} . The three subplots represent average reduction, COP retention, and maximum zone temperature, respectively. Two-dimensional response surfaces of average reduction, COP retention, and maximum zone temperature.

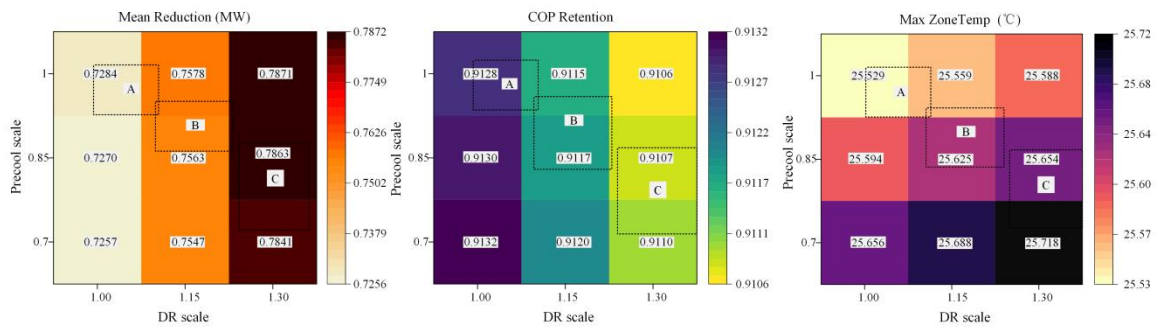


Figure 2. Two-dimensional response surfaces of average reduction, COP retention, and maximum zone temperature.

The response surface results indicate that is the most sensitive parameter for load reduction. A larger generally leads to higher average reduction, but it also lowers COP retention and increases the maximum zone temperature. In contrast, mainly affects comfort-boundary utilization. Lower pre-cooling makes the studied buildings approach the comfort boundary more quickly under DR, whereas stronger pre-cooling provides more thermal buffer but may increase pre-event cooling energy.

To further unveil the optimal compromise among conflicting objectives, Figure 3 presents the Pareto fronts in the response-efficiency and response-comfort planes. While Figure 2 illustrates individual parameter sensitivities, Figure 3 captures the non-dominated trade-off boundaries inherently governing the building cluster. In the response-efficiency plane, the Pareto front indicates that no other tested parameter combination can simultaneously achieve larger average reduction and higher COP retention. In the response-comfort plane, the Pareto front identifies representative conditions between reduction depth and comfort-boundary utilization.

In the tested parameter space, the highest-reduction condition is obtained at $pre_{scale} = 1.0$, $DR_{scale} = 1.3$, and $\tau_{scale} = 0.8$, yielding an average reduction of 0.844 MW with a COP retention of 0.907. By contrast, the highest-efficiency condition is associated with a milder DR intensity and a larger dynamic time constant, reaching a COP retention of 0.919 with a lower average reduction of 0.661 MW. The condition closest to the comfort boundary achieves 0.842 MW reduction with a maximum zone temperature of 25.824 °C. These results further indicate that building flexibility is not a fixed value, but a coordinated

response-efficiency-comfort boundary jointly determined by control aggressiveness, pre-cooling level, and HVAC dynamics.

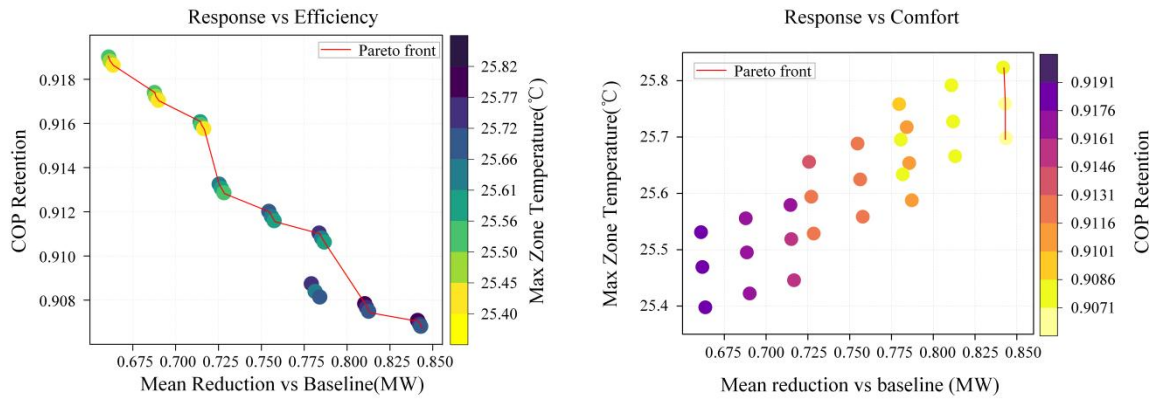


Figure 3. Pareto fronts for response-efficiency and response-comfort relationships.

4. Conclusion

This paper establishes a thermo-electro-efficiency coupled evaluation framework for summer demand response (DR) in grid-interactive commercial buildings. The method integrates explicit multi-zone thermal coupling, HVAC dynamic constraints, and a capacity-PLR-COP correlation. Consequently, it characterizes flexibility through a multidimensional response-efficiency-comfort boundary rather than a scalar reduction value.

Case studies demonstrate that the framework effectively curtails aggregate DR-window power from a 1.769 MW baseline to 1.041 MW under edge-approaching scenarios. In particular, the proposed efficiency-aware strategy yields a 4.6% higher COP retention ratio than aggressive rule-based methods, strictly satisfying indoor comfort limits. A core mechanistic insight is the fundamental trade-off between demand reduction and system efficiency: deep DR inherently depletes the thermal buffer and forces HVAC units into inefficient part-load states. This proves that power reduction metrics alone cannot accurately assess building flexibility.

Ultimately, this framework provides actionable envelopes for peak shaving, virtual storage valuation, and multi-building strategy screening. Future work will transition toward optimization-based real-time coordination, integrate measurement-based parameter identification, and validate the model using field data from diverse commercial buildings.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI-assisted tools only to improve language and readability. The authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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Authors' contribution

Conceptualization, Z.Z. and S.C.; methodology, Z.Z., S.C. and S.H.; software, Z.Z. and Z.G.; validation, Z.Z., H.S. and Z.G.; formal analysis, Z.Z.; investigation, Z.Z. and H.S.; resources, H.S. and Z.G.; data curation, Z.Z. and H.S.; writing—original draft preparation, Z.Z.; writing—review and editing, S.C., H.S., Z.G. and S.H.; visualization, Z.Z.; supervision, S.C. and S.H.; project administration, S.C. and H.S.; funding acquisition, S.C. and H.S. All authors have read and agreed to the published version of the manuscript.

Conflicts of interests

The authors declare that this work was supported by the Science and Technology Project of State Grid Jiangsu Electric Power Co., Ltd. under Grant J2025092. Huiling Su, Zhihui Guo, and Liang Ma are affiliated with commercial or utility organizations as stated in the author affiliations. These affiliations and the funding source did not influence the study design, analysis, interpretation, or reporting of the results. The authors declare no other conflicts of interest.

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