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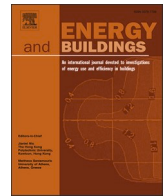
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A practical control strategy for demand flexibility with ensured occupant comfort in grid-interactive efficient buildings

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ABSTRACT

This study proposes a practical and simplified demand response (DR) control strategy from the perspective of grid-interactive efficient buildings (GEBs), aiming to secure demand flexibility while ensuring occupant thermal comfort. Focusing on summer on-peak periods, a linear demand response (LDR) strategy that integrates cooling setpoint adjustment and lighting dimming was designed, and its performance was quantitatively evaluated. A case study was conducted using EnergyPlus-based simulations for a U.S. DOE small office prototype building under summer on-peak weather conditions. Compared with a conventional rapid demand response (RDR) strategy, the proposed LDR approach gradually reduced electrical loads while maintaining occupant thermal comfort indices, including predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), within acceptable comfort ranges. Quantitative analysis of demand flexibility using the grid-interactive impact index (GII) and the flexibility strength index (FSI) showed that the LDR strategy provided approximately 12.5% demand flexibility during DR periods and achieved an electricity cost reduction of about 8.8%. In addition, the results of the part-load ratio (PLR)-based cooling system performance analysis showed that, in the on-peak period, the LDR strategy exhibited improved cooling performance compared with the baseline. Overall, this study shows the potential of a practical DR control strategy that can simultaneously achieve occupant comfort and demand flexibility without relying on complex advanced control technologies.

1. Introduction

In recent years, grid-interactive efficient buildings (GEBs) have emerged as an important issue in the building sector. GEBs have become a key approach for achieving stability and flexibility in electricity demand between the grid and buildings [1]. To achieve this goal, the grid and buildings participate in demand response (DR) programs [2]. DR programs enable bidirectional energy management between the grid and buildings, allowing flexible load variations, balancing energy supply and demand, and improving the stability of power systems [3,4].

To achieve benefits such as supply–demand balance between the grid and buildings through DR programs, various control strategies have been applied. In particular, advanced control techniques such as model predictive control (MPC), data-driven approaches, and agent-based

methods are dominant [5]. The effectiveness of these control techniques has been demonstrated in several previous studies. Furthermore, with the advancement of control technologies, the role of such advanced control methods in DR programs has been further strengthened.

Despite these advantages, the practical application of advanced control techniques in real-world settings remains very limited due to high infrastructure costs, operational complexity, and high maintenance requirements [6,7]. Therefore, in complex systems involving equipment and communication between the grid and buildings, DR programs should be controlled in a more realistic and practical manner [8].

Moreover, DR programs often overlook occupant comfort. While securing flexibility and stability between the grid and buildings is a critical requirement for achieving GEBs, occupant comfort should not be neglected [9]. That is, when a DR program is activated to secure demand flexibility, buildings are required to perform flexibility control while

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Nomenclature		T_{freeze}	Cooling setpoint at which control is frozen, (°C)
Abbreviations		t_0	DR start time, (h)
ABC	Agent-based control	t_1	DR end time, (h)
BAS	Building automation system	t_R	End time of the recovery period, (h)
BEMS	Building energy management system	$r_{\uparrow}$	Linear temperature increase rate, (°C/h)
COP	Coefficient of performance	$r_{\downarrow}$	Linear temperature decrease rate, (°C/h)
DFC	Demand flexibility capacity	$L_{set}(t)$	Lighting density ratio at time t , (–)
DFI	Demand flexibility intensity	$L_{baseline}$	Lighting density ratio immediately before DR, (–)
DFP	Demand flexibility percentage	L_{target}	Target lighting density ratio during DR, (–)
DOE	Department of Energy	$L_{original}$	Original lighting density before DR, (–)
DR	Demand response	$S_{\uparrow}$	Linear dimming increase rate, (–)
ESS	Energy storage system	$S_{\downarrow}$	Linear dimming decrease rate, (–)
FSI	Flexibility strength index	Thermal Comfort	
GEB	Grid-interactive efficient buildings	M	Metabolic rate, (W/m ²)
GII	Grid-interactive impact index	W	Effective mechanical power, (W/m ²)
HVAC	Heating, ventilation, and air conditioning	I_{cl}	Clothing insulation, (m ² •K/W)
LDR	Linear demand response	f_{cl}	Clothing surface area factor, (–)
MPC	Model predictive control	t_a	Air temperature, (°C)
PLR	Part load ratio	t_r	Mean radiant temperature, (°C)
PMV	Predicted mean vote	v_{ar}	Relative air velocity, (m/s)
PPD	Predicted percentage of dissatisfied	P_a	Water vapor partial pressure, (Pa)
PV	Photovoltaic	h_c	Convective heat transfer coefficient, (W/ m ² •K)
RDR	Rapid demand response	t_{cl}	Clothing surface temperature (°C)
SRI	Satisfied reduction intensity	Demand Flexibility and Grid Interaction	
TRI	Total reduction intensity	P_{exp}	Amount of electricity exported from building to grid, (kW)
Symbols, Control and Strategy		P_{imp}	Amount of electricity imported from grid to building, (kW)
$T_{set}(t)$	Cooling setpoint as time t , (°C)	$P_{Baseline}$	Baseline electric power usage, (kW)
$T_{baseline}$	Cooling setpoint immediately before DR, (°C)	$P_{DRcontrol}$	Electric power usage under DR control, (kW)
T_{target}	Target cooling setpoint during DR, (°C)	t_1, t_2	Start and end times of the evaluation period, (h)
$T_{original}$	Original cooling setpoint before DR, (°C)		

simultaneously ensuring occupant comfort [10]. Despite noticeable progress toward GEBs to achieve stability and flexibility in electricity demand between the grid and buildings, existing DR control strategies for demand flexibility remain either overly complex or insufficient in satisfying occupant comfort [11].

To address these challenges, this study proposes a practical and simplified DR control strategy that can secure demand flexibility while ensuring occupant comfort. In particular, this study investigates an integrated approach combining cooling setpoint control and lighting control during summer periods when electricity demand reaches its peak. In addition, this study considers not only control within an acceptable comfort range for occupants but also comfort conditions in which discomfort remains undetectable during DR programs. The main contributions of this study are summarized as follows:

- A practical and simplified DR control strategy is proposed.
- During DR programs, occupant thermal and visual comfort are ensured by controlling discomfort at acceptable and undetectable levels.
- The interaction impact between the grid and buildings and demand flexibility are quantitatively evaluated.

In this study, 'practical' also refers to the simplicity of implementation in existing building control environments. Specifically, the proposed strategy can be configured using standard building automation system (BAS) or building energy management system (BEMS) functions, such as cooling setpoint scheduling and lighting control. This does not require online optimization or high-fidelity predictive models.

Unlike MPC-based approaches, which rely on predictive models and online optimization, the proposed strategy prioritizes simplicity of

implementation, reduces computational burden and compatibility with existing building control environments. Therefore, rather than demonstrating superiority over advanced, optimization-based control in all conditions, this study aims to examine whether a deployable, rule-based strategy can secure meaningful demand flexibility while maintaining occupant comfort.

2. Related works

2.1. DR control strategies

For the effective implementation of DR, it is necessary to identify various flexibility resources within buildings and control them precisely [12]. Building energy systems are nonlinear and involve multivariable interactions and unpredictable disturbances [13,14]. Therefore, it is difficult to sufficiently secure the dynamic load adjustment capability required for DR using simple control approaches alone [15]. In this context, model predictive control (MPC) has become the most widely used advanced control technique in studies related to DR control strategies for GEBs [16]. This technique is clearly distinguished from conventional PID-based control in that it predicts future system states based on a system model and repeatedly computes optimal control inputs accordingly.

Previous literature reviews have shown that MPC accounts for more than 76% of GEB control studies involving DR, which suggests that its predictive performance and constraint-based optimization capability exhibit high compatibility with the requirements of DR [5]. For example, heating and cooling control using MPC has achieved approximately 13–16% cost savings and about 25% electricity savings compared with conventional PID-based approaches [17,18]. Since DR

requirements such as load shifting, energy storage system (ESS) charging and discharging scheduling, and setpoint optimization directly align with the predictive capability and constraint-based optimization structure of MPC, MPC has emerged as the most extensively studied DR control technique to date [19].

In addition, given that building energy systems are complex systems comprising multiple devices, zones, and resources, agent-based control (ABC) has also been investigated as a promising approach for DR. ABC models subsystems within a building as independent agents to form a decentralized decision-making structure and shows high potential, particularly in DR contexts that require the integrated control of various resources such as photovoltaic systems (PV), ESS, and heating, ventilation, and air conditioning (HVAC) systems. However, structural limitations remain, including difficulties in agent coordination and achieving global optimization, which continue to constrain its practical implementation [5].

Although existing DR control techniques presented in the literature demonstrate substantial theoretical performance, their application in real buildings remains limited. The primary reasons include the high computational burden of advanced control algorithms, the cost of model development and maintenance, communication infrastructure requirements, and limitations in accounting for uncertainties such as occupant behavior. In addition, most existing studies focus mainly on improving the intrinsic performance of control methods, resulting in insufficient consideration of practical operating conditions required for real-world deployment. Therefore, this study aims to propose a simple and practical control strategy that can maximize DR performance while being operable and applicable within the current level of building control practice.

In summary, while these studies demonstrate strong theoretical performance, they generally require significant modelling efforts, computational resources and communication infrastructure, which could impede their implementation in existing buildings. Therefore, there is still a clear gap between the optimality of control in literature and its practical operability in real-world building environments.

2.2. Impact of DR programs on occupant comfort

DR programs alter building loads through measures such as increasing heating and cooling setpoints, adjusting HVAC output, and applying lighting on/off and dimming controls, thereby directly affecting occupants' thermal and visual comfort. Aghniaey and Lawrence pointed out that while existing studies emphasize the load reduction effects of DR, they often fail to sufficiently consider the fact that elevated setpoints can induce thermal discomfort, fatigue, and deterioration of indoor air quality [11]. In particular, negative occupant responses have been repeatedly reported at temperatures above 28°C, and the rate and duration of setpoint changes have also been shown to have significant impacts on comfort.

In an experimental study by Zhao et al., occupant responses were observed by simulating DR conditions and varying indoor temperatures from 23 to 29°C [10]. The results showed that the temperature range of 23 to 27°C was acceptable to most occupants, whereas a clear degradation in comfort was observed at 29°C. In addition, even under the same thermal conditions, the duration for which comfort was maintained varied significantly depending on individual acceptable thermal levels, and adaptive behaviors such as the use of fans and changes in clothing were found to be effective in mitigating increases in discomfort.

For lighting-based DR, Akashi and Neches reported that when gradual dimming control is applied, there exists a 'undetectable' region in which occupants do not perceive the change itself, and that a certain level of illuminance reduction does not significantly affect visual performance or acceptability [20]. This finding suggests that load reduction at an undetectable level is also feasible in lighting-based DR.

Recent studies on DR control have incorporated comfort into objective functions by quantifying whether indoor temperature remains

within a comfort band; however, occupant comfort still varies depending on model uncertainty and building characteristics, and most studies remain focused on minimizing acceptable discomfort [21]. Therefore, this study aims to develop a control strategy that maintains occupant comfort by controlling discomfort at a 'undetectable' level within the 'acceptable' comfort range.

In summary, previous DR studies have primarily focused on maintaining comfort within an acceptable range. However, relatively little attention has been given to whether occupants can detect the environmental changes induced by control. This is a particularly important limitation in the practical operation of DR, where abrupt but technically acceptable control actions may still be perceived negatively by occupants.

2.3. Quantification of demand flexibility between grid and buildings

The quantification of demand flexibility is a key process for evaluating the extent to which buildings possess load adjustment capabilities during DR events, and various quantitative indicators have been proposed for this purpose [22].

Li et al. distinguished between the total reduction intensity (TRI) and the satisfied reduction intensity (SRI), enabling the evaluation of the extent to which DR actions are effective while meeting occupant requirements. This approach is useful in that it allows the reduction potential and the acceptable reduction range to be interpreted separately [23].

In addition, Han et al. proposed demand flexibility capacity (DFC), demand flexibility intensity (DFI), and demand flexibility percentage (DFP) for application in GEBs consisting of multiple buildings, thereby enabling quantitative comparisons of flexibility among buildings of different scales and functions. In particular, by utilizing measurement-based data from 1,249 load points, various loads such as heating, cooling, ventilation, domestic hot water, and lighting were automatically classified and quantified, allowing the DR potential of building clusters to be assessed from an aggregated resource perspective [24].

Meanwhile, attempts have been made to identify and analyze the contribution of hidden (fundamental) factors to flexibility, such as internal thermal mass, furnishings, HVAC operational characteristics, and occupant behavior. Chen et al. modeled thermal mass, storage tanks, lighting, electrical equipment, and occupant behavior as independent flexibility resources and calculated the total electrical flexibility, quantitatively demonstrating that flexibility originates not only from controllable equipment ranges but also from the physical and behavioral characteristics of buildings [25].

Furthermore, Zhou et al. introduced metrics such as forced/delayed flexibility, flexibility factor, and on-site flexible renewable fraction for complex systems incorporating renewable energy, hybrid storage systems, and multi-energy conversion configurations, thereby evaluating the temporal energy flow shifting capability in a multidimensional manner [26]. This approach captures system-level flexibility that extends beyond single-load control to include interactions among buildings, storage systems, and networks.

As summarized above, existing studies have quantified demand flexibility from different perspectives, including load-specific reduction performance (TRI/SRI), cross-building comparisons (DFC/DFI/DFP), decomposition of intrinsic resources, and hybrid system-based flexibility. While these studies provide useful flexibility indicators from different perspectives, fewer studies have integrated such quantitative metrics with a DR control strategy that is both practically implementable and aware of occupant comfort within a single case-study framework. Consequently, the relationship between flexibility quantification and deployable control design remains inadequately addressed in existing literature. Building upon these individual quantification frameworks, this study aims to provide an integrated evaluation of the overall performance of GEBs in their interaction with the power grid by simultaneously analyzing the achievable DR potential on the demand

side (demand flexibility) and the grid interaction on the supply side (grid impact).

3. Methodology

3.1. Overall research process

This section describes the overall research process. The study is grouped into four main research steps. Fig. 1 shows an overview of the overall research process.

Step 1: The first step was to determine the case study building. In this study, a small office building provided by the U.S. DOE commercial building prototypes was selected. Based on the selected building, flexibility loads were identified and defined as controllable resources under the DR scenario.

Step 2: The second step was to configure the DR scenario. In this study, a specific day with peak cooling demand was selected, and a scenario was established in which DR reduction commands were issued during the on-peak period. At the time when the DR command was activated, cooling setpoint control of the HVAC system and lighting dimming were applied to satisfy the DR requirements.

Step 3: The third step was to analyze occupant comfort. The analysis was conducted using representative thermal comfort indices, namely predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD). In this step, visual comfort was not analyzed, as it was assumed to be always satisfied.

Step 4: The final step was to quantitatively evaluate flexibility between the grid and buildings. Grid-interaction impact and flexibility strength were calculated and quantitatively assessed.

In the present study, the DR strategy was not designed to track a predefined energy reduction target. Instead, practical control actions were prescribed in advance and the resulting reduction in demand was evaluated relative to the baseline case. In addition, the indoor thermal response was evaluated using a dynamic EnergyPlus simulation. In this environment, the air temperature in each zone evolves through transient heat balance calculations that reflect the thermal properties of the building envelope, internal gains, weather conditions and HVAC operation. Consequently, the PMV and PPD results in this study were derived from the dynamically simulated indoor thermal conditions, rather than static temperature assumptions.

3.2. Case study description

3.2.1. Target building

In this study, a small office prototype developed by the U.S.

Department of Energy (DOE) was selected as the target building for the case study [27]. The building consists of four perimeter zones and one core zone, with a total floor area of approximately 510 m². To conduct the case study in Daejeon, South Korea, simulations were performed using local weather data for this region. Fig. 2 shows the geometry and five-zone configuration of the target building. This provides the physical basis for the subsequent zone-level thermal comfort analysis and dynamic response (DR) control evaluation. Table 1 summarizes the thermal and system characteristics of the target building.

3.2.2. Configuration of DR scenario

This section describes the control scenarios implemented in buildings in response to DR signals. Because the objective of this study is to achieve practical and simplified control while satisfying occupants' thermal and visual comfort, cooling setpoint control and lighting dimming were adopted. One feasible implementation approach is to integrate the proposed strategy into the supervisory layer of an existing BAS or BEMS platform, whereby a DR event signal would activate a predefined control routine. This routine would allow the system to automatically adjust the zone cooling setpoint schedule according to the specified ramp rate and apply the corresponding lighting dimming ratio during the designated DR period. Within this framework, operators would primarily manage a limited number of parameters, such as the DR time window, temperature ramp rate, recovery period and target dimming level, via the BAS or BEMS interface. Meanwhile, lower-level local controllers would continue to perform the actual equipment-level control.

The DR control strategy implemented a load shedding strategy for a duration of 3 h centered on the on-peak period from 13:00 to 16:00. This duration was determined by considering the typical duration (1 to 4 h) of standard DR programs in South Korea, as reported in previous studies [24].

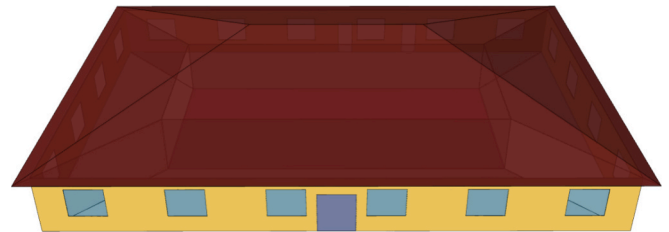


Fig. 2. The geometry and five-zone configuration of the building used in the zone-level thermal comfort analysis and DR control evaluation.

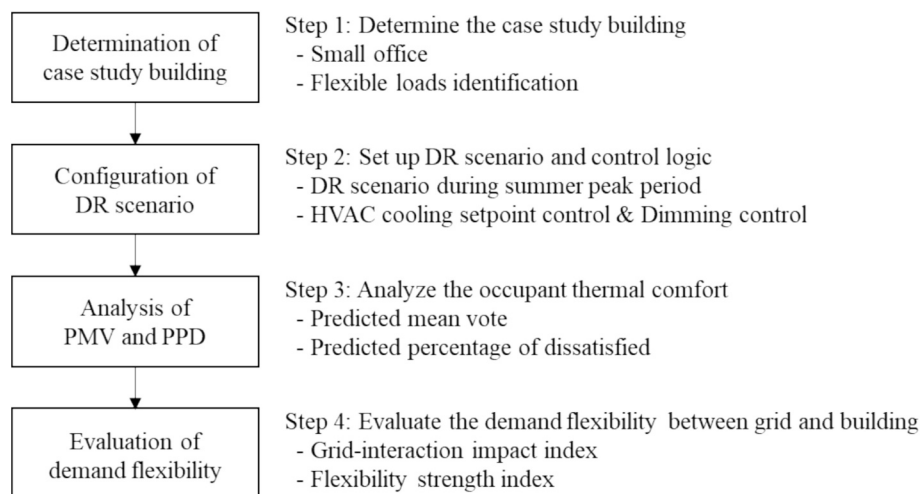


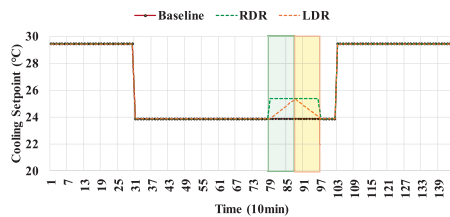
Fig. 1. Overview of the overall research process

Table 1
Characteristics of the target building for case study.

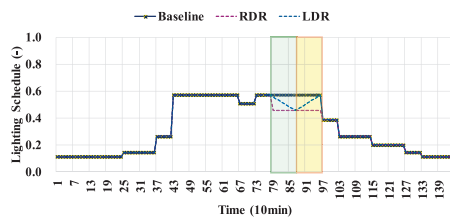
Category	Classification	Values
Building	Thermal transmittance (W/m ² K)	Exterior wall
		Interior wall
		Ceiling
		Roof
		Floor
		Window
		Exterior door
		WWR (Window to Wall Ratio) (%)
		Number of Floors (–)
		Floor to floor height (m)
System (Air-source heat pump)	Capacity (W)	Cooling
		Heating
	COP (Coefficient of Performance) (–)	Cooling
		Heating
	Setpoint (°C)	Cooling
		Heating
	Setback (°C)	Heating
		Cooling

The DR control strategies were classified into two types: rapid DR (RDR) and linear DR (LDR). RDR is a conventional DR shedding strategy in which DR resources, such as the cooling setpoint and lighting density ratio, are adjusted immediately upon receiving a DR signal. In contrast, LDR is a strategy in which DR resources are controlled smoothly and linearly by dividing the control period into a start period and a recovery period. This strategy was designed to control occupant comfort within an acceptable level while simultaneously ensuring that discomfort remains undetectable. Although maintaining occupant comfort within an acceptable level is essential, abrupt control changes may cause occupants to perceive the change instantaneously and experience discomfort. Therefore, occupant comfort can be regarded as being secured only when comfort is controlled within an acceptable level while discomfort is controlled at an undetectable level [28].

In this study, the LDR strategy was adopted as a means of ensuring occupant comfort, and its effectiveness was evaluated through a comparative analysis with the conventional RDR strategy. Fig. 3 illustrates the cooling setpoint and lighting density dimming control



(a) Cooling setpoint



(b) Lighting schedule

Fig. 3. Demand response strategies for demand flexibility.

strategies in response to DR signals on a representative summer peak day. The green and yellow boxes indicate the 3 h DR duration, and in the LDR strategy, they represent the DR start period and the recovery period, respectively.

The LDR control logic for ensuring occupant comfort is formulated as shown in equation (1). The equation (1) represents the cooling setpoint control strategy designed to ensure occupants' thermal comfort, in which the cooling setpoint is controlled linearly at a rate of 0.5°C/h. This temperature change rate has been experimentally validated in several previous studies as maintaining discomfort at an undetectable level for occupants [29–31]. However, when the temperature change rate is set higher than 0.5°C/h, the control strategy shown in equation (3) can be applied. This strategy freezes the cooling setpoint once occupants' thermal comfort exceeds the comfort range ($-0.5 < PMV < +0.5$ or $PPD < 10\%$), and it serves as a practical and simplified approach to compensate for the penalty associated with higher temperature change rates. As this auxiliary strategy is feedback-triggered, its practical implementation would require hysteresis bands or minimum dwell-time constraints to prevent excessive switching near the comfort boundary. However, this mechanism was not employed in the primary simulation scenario of the present study, which adopted a fixed linear ramp of 0.5°C/h in Eq. (1).

In this study, Eq. (1) was used as a predefined rule-based control trajectory rather than as the solution of an online optimization problem. The ramp rate of 0.5°C/h was selected from previous comfort-related studies as a practical design parameter for maintaining minimally perceptible thermal change. In general, air-handling unit setpoint control is implemented using room controllers with stepwise control within a certain range (e.g., increments of 0.5°C); however, this study assumed that fine-grained linear control was feasible. Three LDR strategies are presented below, and in this study, strategy i) was adopted for the cooling setpoint, while strategy iii) was adopted for lighting density (dimming) control.

i) Linear control of the cooling setpoint at 0.5°C/h

$$T_{set}(t) = \begin{cases} T_{baseline} + r_1(t - t_0), & t_0 \leq t < t_1 \\ T_{target} - r_1(t - t_1), & t_1 \leq t < t_R \\ T_{original}(t), & \text{otherwise} \end{cases} \quad (1)$$

$$r_1 = \min\left(0.5, \frac{T_{target} - T_{baseline}}{t_1 - t_0}\right), r_1 = \min\left(0.5, \frac{T_{target} - T_{original}}{t_R - t_1}\right) \quad (2)$$

where, $T_{set}(t)$ is the cooling setpoint, $T_{baseline}$ is the cooling setpoint immediately before DR, T_{target} is the target cooling setpoint during DR, $T_{original}$ is the original cooling setpoint before DR, t_0 is the DR start time, t_1 is the DR end time, t_R is the end time of the recovery period, and r_1 and r_1 are the linear temperature change rates (0.5°C/h).

ii) Linear control of the cooling setpoint at r_1^{max}

$$T_{set}(t) = \begin{cases} T_{baseline} + r_1(t - t_0), & t_0 \leq t < t_v \\ T_{freeze}, & t_v \leq t < t_1 \\ T_{freeze} - r_1(t - t_1), & t_1 \leq t < t_R \\ T_{original}(t) - r_1(t - t_1), & \text{otherwise} \end{cases} \quad (3)$$

$$t_v = \min\{t \in [t_0, t_1] | PMV(t) \notin [PMV_{min}, PMV_{max}] \text{ or } PPD(t) > PPD_{max}\} \quad (4)$$

$$r_1 = \min\left(r_1^{max}, \frac{T_{freeze} - T_{baseline}}{t_1 - t_0}\right), r_1 = \min\left(r_1^{max}, \frac{T_{freeze} - T_{recovery}}{t_R - t_1}\right) \quad (5)$$

where, T_{freeze} is the cooling setpoint at which control is frozen when occupant discomfort is detected. This control strategy is not recommended because occupants may detect discomfort; it is suggested only when it is unavoidable to significantly increase the temperature change rate.

At the same time, the lighting dimming control logic is defined as

shown in Eq. (6). Previous studies have validated that a 20% reduction in lighting is acceptable and undetectable for occupants; therefore, in this study, the target lighting reduction rate was set to 20% and controlled linearly [20,32]. Only the 20% lighting reduction strategy, which does not induce dissatisfaction in visual comfort, was considered in this study. However, this 20% dimming threshold was adopted as a representative value for a generic office setting and does not explicitly consider the heterogeneity associated with factors such as occupant age, the type of visual task being performed, and the characteristics of how space is used.

iii) Linear dimming control to reduce the lighting density by 20%

$$L_{set}(t) = \begin{cases} L_{baseline} - s_1(t - t_0), & t_0 \leq t < t_1 \\ L_{target} + s_1(t - t_1), & t_1 \leq t < t_R \\ L_{original}(t), & \text{otherwise} \end{cases} \quad (6)$$

$$s_1 = \min(0.8, \frac{L_{baseline} - L_{target}}{t_1 - t_0}), s_1 = \min(0.8, \frac{L_{original} - L_{target}}{t_R - t_1}) \quad (7)$$

where, $L_{set}(t)$ is the lighting density ratio, $L_{baseline}$ is the lighting density ratio immediately before DR, L_{target} is the target lighting density ratio during DR, $L_{original}$ is the original lighting density ratio before DR, and s_1 and s_1 are the linear dimming rates (20% reduction).

Although optimization-based extensions such as convex reformulation and model predictive heuristic control may improve adaptability under more complex operating conditions, such methods were beyond the scope of this rule-based study.

3.3. Thermal comfort model

In this study, predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD), which are representative thermal comfort indices, were analyzed to evaluate changes in occupants' thermal comfort resulting from cooling setpoint control [33]. Visual comfort was not evaluated because only a 20% lighting dimming strategy, which is assumed to cause no dissatisfaction, was applied. Therefore, the visual comfort assumption in this study should be interpreted as a simplified condition based on an office scenario supported by literature, rather than as a threshold applicable to all occupants and tasks. Accordingly, only thermal comfort was assessed.

3.3.1. Predicted mean vote

The PMV index proposed by Fanger represents the predicted mean value of votes from a large group of occupants exposed to the same environment on a seven-point thermal sensitivity scale ranging from -3 to +3 [33]. In general, a PMV range from -0.5 to +0.5 is defined as the acceptable level of thermal sensitivity [34]. thermal sensitivity In this thermal sensitivity scale, negative values indicate cooler sensations, while positive values indicate warmer sensations. The PMV index was calculated using equation (8), which expresses the thermal balance of the human body as a function of personal variables (metabolic rate, clothing insulation, and mechanical work) and environmental variables (air temperature, mean radiant temperature, air velocity, and air humidity). The table below illustrates the relationship between the PMV index and thermal sensitivity, and PMV is calculated using the following equation (Table 2).

$$PMV = (0.303 \times \exp^{-0.036M} + 0.028)$$

Table 2

Relationship between PMV index and thermal sensitivity.

Thermal Sensitivity	Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot
PMV	-3	-2	-1	0	+1	+2	+3

$$\begin{aligned} & \times \{ (M - W) - 3.05 \times 10^{-3} \times [5733 - 6.99 \times (M - W) - P_a] \\ & - 0.42 \times [(M - W) - 58.15] - 1.7 \times 10^{-5} \times M \times (5867 - P_a) \\ & - 0.0014 \times M \times (34 - t_a) - 3.96 \times 10^{-8} \times f_{cl} \\ & \times [(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4] - f_{cl} \times h_c \times (t_{cl} - t_a) \} \end{aligned} \quad (8)$$

$$\begin{aligned} t_{cl} &= 35.7 - 0.028 \times (M - W) - I_{cl} \times \{ 3.96 \times 10^{-8} \times f_{cl} \\ & \times [(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4] + f_{cl} \times h_c \times (t_{cl} - t_a) \} \end{aligned} \quad (9)$$

$$h_c = \begin{cases} 2.38 \times |t_{cl} - t_a|^{0.25} \text{ for } 2.38 \times |t_{cl} - t_a|^{0.25} > 12.1 \times \sqrt{v_{ar}} \\ 12.1 \times \sqrt{v_{ar}} \text{ for } 2.38 \times |t_{cl} - t_a|^{0.25} < 12.1 \times \sqrt{v_{ar}} \end{cases} \quad (10)$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 \times I_{cl} \text{ for } I_{cl} \leq 0.078 \text{ m}^2 \times K/W \\ 1.05 + 0.645 \times I_{cl} \text{ for } I_{cl} > 0.078 \text{ m}^2 \times K/W \end{cases} \quad (11)$$

where, M is the metabolic rate, W is the effective mechanical power, I_{cl} is the clothing insulation, f_{cl} is the clothing surface area factor, t_a is the air temperature, $\bar{t}_r$ is the mean radiant temperature, v_{ar} is the relative air velocity, P_a is the water vapour partial pressure, h_c is the convective heat transfer coefficient, and t_{cl} is the clothing surface temperature.

3.3.2. Predicted percentage of dissatisfied

The predicted percentage of dissatisfied (PPD) represents the proportion of occupants who are thermally dissatisfied within a large group exposed to the same environment. Because PPD reflects the dispersion of individual thermal votes arising from human factors, it allows thermal comfort to be analyzed in a more quantitative manner than PMV. In general, a PPD value within 10% is defined as the acceptable level of thermal sensitivity [34]. PPD is dependent on PMV and is calculated using the following equation.

$$PPD = 100 - 95 \times \exp(-0.003353 \times PMV^4 - 0.2179 \times PMV^2) \quad (12)$$

3.4. Quantitative evaluation metrics for demand flexibility

Because maintaining the balance between demand and supply is critical in GEBs, it is essential to quantitatively analyze flexibility under grid-connected conditions. Accordingly, this study analyzed demand flexibility and grid impact using quantitative evaluation metrics.

3.4.1. Grid-interactive impact index

The grid-interactive impact index (GII) is a performance metric that enables the quantitative evaluation of bidirectional power interactions between the grid and buildings [35]. Specifically, it represents the proportion of the total amount of electricity exchanged between a building and the external grid relative to the building's total electricity demand, thereby indicating the degree to which the building interacts with the grid. A higher GII value indicates stronger interaction between the building and the grid, whereas a lower value indicates a higher level of self-consumption within the building. In cases where there is no on-site generation or storage and no electricity export, GII should be interpreted more narrowly as an indicator of grid dependence and import-side electricity exchange during the evaluation period, rather than as a complete metric of bidirectional flexibility.

$$\alpha_{GII}^{(b)} = \frac{\int_{t_1}^{t_2} P_{exp}^{(b)}(t) dt + \int_{t_1}^{t_2} P_{imp}^{(b)}(t) dt}{\int_{t_1}^{t_2} P_{Baseline}^{(b)}(t) dt} \times 100 \quad (13)$$

where $P_{exp}^{(b)}$ is the amount of electricity exported from the building to grid, $P_{imp}^{(b)}$ is the amount of electricity imported from the grid to building.

3.4.2. Flexibility strength index

The flexibility strength index (FSI) refers to the reduction percentage in cumulative electric power usage of a building during the evaluation period, compared to the baseline power usage after the introduction of a DR control strategy. This index accurately reflects the impact of DR control strategies for DF on the total electric power usage of buildings. In other words, it is a quantitative measure of the effect of DR scenarios [36]. The higher the FSI value, the greater the electric power savings achieved through DR control during the evaluation period. The equation is as follows:

$$\varphi_{FSI}^{(b)} = \frac{\int_{t_1}^{t_2} P_{Baseline}^{(b)}(t)dt - \int_{t_1}^{t_2} P_{DRcontrol}^{(b)}(t)dt}{\int_{t_1}^{t_2} P_{Baseline}^{(b)}(t)dt} \times 100 \quad (14)$$

where $P_{Baseline}^{(b)}$ is the baseline electric power usage in building b , and t is the evaluation period during which the DR control strategy is implemented. In previous studies, the FSI has typically not exceeded 40%, and has been subdivided into four stages ($0\% < FSI \leq 10\%$: weak flexibility, $10\% \leq FSI < 20\%$: relatively strong flexibility, $20\% \leq FSI < 30\%$: strong flexibility, $30\% \leq FSI$: extremely strong flexibility) [36].

4. Results and discussions

This section presents the simulation results of the DR scenarios applied to the small office building. The analysis was grouped into six categories: load profile, occupant thermal comfort, interaction impact between the grid and the building, electricity power consumption, electricity cost, and cooling system performance. For this purpose, a summer peak-load day (July 24) in Daejeon, South Korea, was selected as the simulation date.

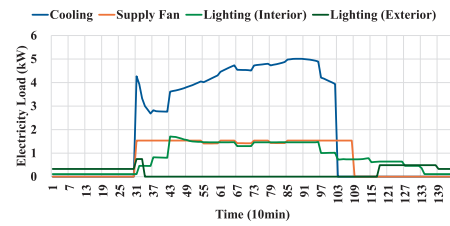
4.1. Load profile

To implement building control under DR scenarios in GEBs, it is essential to identify controllable electrical loads and to analyze their load profiles in advance. In the target building of this study, the controllable flexibility-related electrical loads were cooling, supply fans, and lighting; therefore, the analysis was conducted using only these electrical loads. In contrast, domestic hot water loads were operated using natural gas, and ventilation was provided solely through natural ventilation.

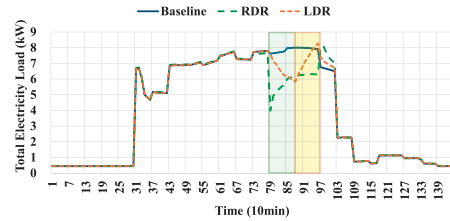
For lighting, only interior lighting loads, excluding exterior lighting, were included in the 'linear dimming control to reduce the lighting density by 20%' strategy. Fig. 4 illustrates the individual electrical load profiles during the peak cooling period as well as the total electrical load profiles under the DR scenarios.

In the baseline electricity load profile, the cooling load was the largest during the peak period from 13:00 to 16:00, reaching a maximum of approximately 5 kW, while the associated supply fan load remained at around 1.5 kW. For lighting loads, interior lighting varied according to the occupancy schedule, whereas exterior lighting was observed to be turned on during nighttime periods when occupants were not present. Therefore, in accordance with the objective of proposing a DR strategy that ensures occupant comfort, exterior lighting loads were not included in the DR control strategy in this study.

Under the RDR strategy, the total electricity load decreased by more than approximately 50%, from 8 kW to 4 kW, at the DR start time and then gradually rebounded. In contrast, under the LDR strategy, the slope of the total electricity load decreased smoothly at the DR start time and exhibited a gradual rebound during the recovery period. While the RDR strategy was able to achieve a large reduction in electricity demand at the DR start time, it may exacerbate power instability; conversely, the LDR strategy is considered capable of securing stability by reducing electricity demand in a smooth manner.



(a) Baseline electricity load profile for each flexibility load



(b) Total electricity load profile for each DR strategy

Fig. 4. Electricity load profile of demand flexibility resources by DR strategies during peak cooling period.

4.2. Occupant thermal comfort

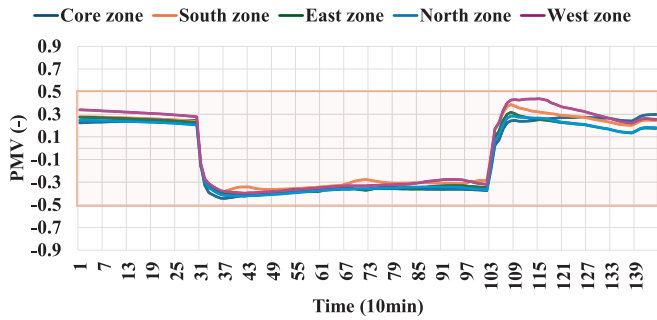
Occupant thermal comfort is generally defined as the range in which PMV lies between -0.5 and $+0.5$ and PPD remains below 10%. In the figures below, this comfort range is indicated by the orange semi-transparent box. In this section, PMV and PPD for each zone under the two DR strategies were derived through simulations, and the effectiveness of the DR strategies was demonstrated through comparison with the baseline. Fig. 5 shows the variations in PMV under the baseline and the two DR strategies.

The PMV analysis showed that, under the baseline, all five zones, including the core zone, satisfied the comfort range. Under the RDR strategy, PMV exhibited a rapid increase from approximately -0.3 to a maximum of about 0.1 at the DR start time. This behavior resulted from the abrupt increase in the cooling setpoint. In such cases, occupants experience a rapid change in body temperature over a short period, which may lead to discomfort or allow occupants to perceive changes in comfort conditions.

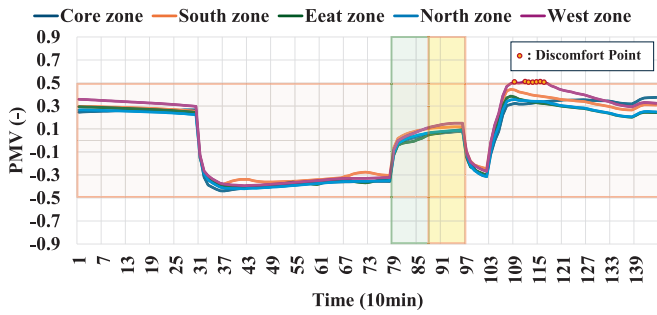
In contrast, under the LDR strategy, PMV changed smoothly from the DR start time through the recovery period, and occupants were considered less likely to detect discomfort compared with the RDR strategy. In particular, after the DR program ended, PMV under the LDR strategy remained within the comfort range, whereas under the RDR strategy, the PMV in the west zone deviated from the comfort range after HVAC system off condition. This phenomenon appears to have occurred because the rapid increase in the cooling setpoint during the DR program prevented PMV from returning to a stabilized level even after the DR event ended. For the west zone, it is common for solar radiation to affect indoor conditions during the afternoon when the system is turned off, which likely caused PMV to exceed the upper comfort threshold of $+0.5$. Therefore, to satisfy both conditions of 'acceptable' thermal comfort and 'undetectable' changes in thermal comfort, the LDR strategy can be considered more flexible than the RDR strategy.

Fig. 6 presents the changes in PPD under the baseline and the two DR strategies.

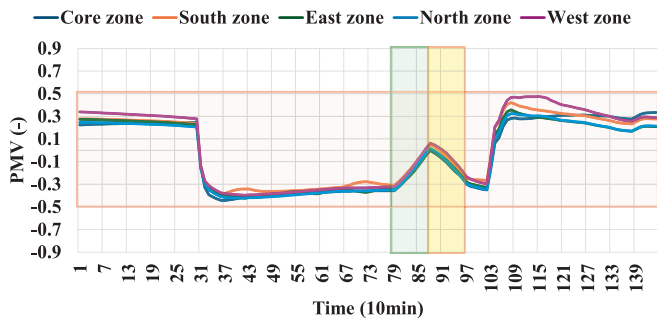
The PPD analysis results were very similar to those of the PMV analysis. For both the baseline and the LDR strategy, PPD remained within the comfort range even after the DR program ended. In contrast, under the RDR strategy, PPD did not return to a stabilized level after the DR program ended, and consequently, periods in which PPD exceeded 10% were observed during the afternoon after HVAC system off



(a) Baseline

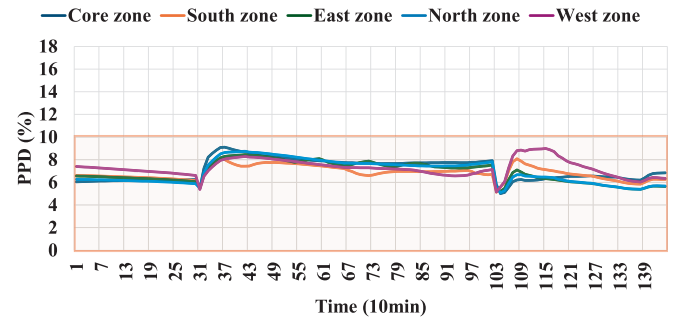


(b) RDR

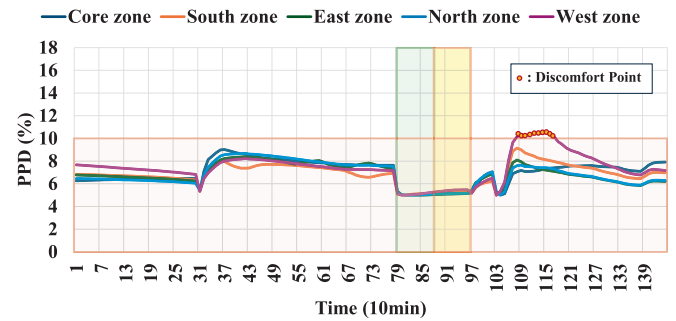


(c) LDR

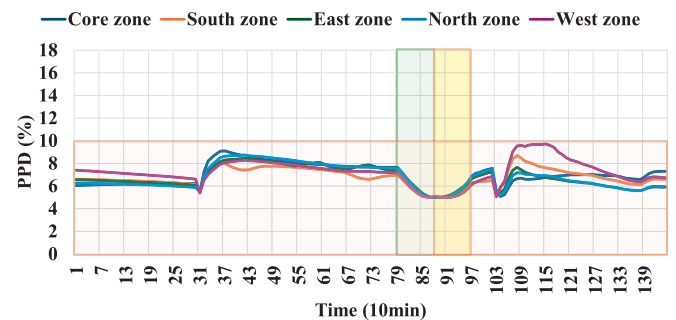
Fig. 5. PMV changes by DR strategies.



(a) Baseline



(b) RDR



(c) LDR

Fig. 6. PPD changes by DR strategies.

condition. Therefore, from the perspective of a combined analysis of PMV and PPD, the LDR strategy can be considered more suitable than the RDR strategy for ensuring occupants' thermal comfort.

4.3. Interaction impact between grid and building

This section analyzed the interaction impact between the grid and the building under the two DR strategies. For this purpose, the GII introduced in Section 3.4.1 was used. From the perspective of zero-energy buildings, a lower GII value is considered favorable because it indicates a higher level of energy self-consumption. However, in South Korea, existing buildings older than 20 years account for approximately 60% of the total building stock compared with newly constructed buildings, making it difficult to rapidly transition to zero-energy buildings [37]. For this reason, policies related to zero-energy buildings in South Korea have been implemented through a phased roadmap

extending to 2050 [38]. Therefore, at the current stage, which corresponds to the initial phase of the zero-energy building roadmap, a higher GII value can instead indicate enhanced interaction with the grid and, consequently, greater potential for improving overall DR performance. Fig. 7 shows the GII values of the two DR strategies during the DR period.

The GII analysis results showed that the GII was 82.3% for the RDR strategy and 90.0% for the LDR strategy. In the case of RDR, electricity demand itself decreased sharply during the DR program due to the abrupt increase in the cooling setpoint and the reduction in lighting density. As a result, the amount of electricity exchanged with the grid was reduced, leading to a lower GII value compared with the LDR strategy. In contrast, under the LDR strategy, electricity demand was reduced to a lesser extent than under RDR, resulting in a higher potential for electricity exchange with the grid. Accordingly, the higher GII observed under the LDR strategy in this study indicates a greater

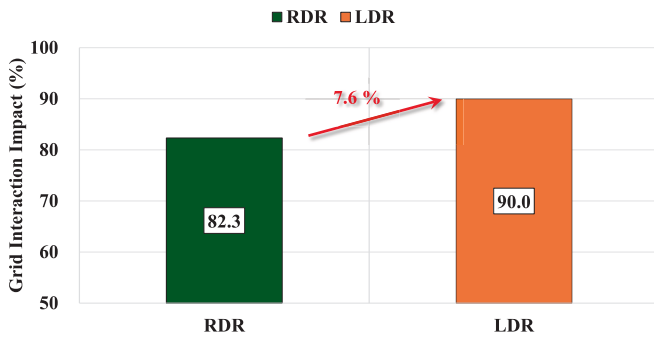


Fig. 7. Grid interaction impact by each DR control strategy.

tendency for grid interaction under import-dominant operation rather than superior bidirectional flexibility in the strict sense.

4.4. Demand flexibility and electricity power consumption

This section analyzed the demand flexibility of the LDR strategy, whose effectiveness was demonstrated in Sections 4.2 and 4.3, in comparison with the baseline case. For this purpose, the FSI introduced in Section 3.4.2 was used. Fig. 8 presents the FSI analysis results representing the demand flexibility of the LDR strategy during the DR period.

The FSI analysis results for the LDR strategy during the DR period showed a value of approximately 12.5%. In addition, the analysis of total electricity power reduction for each flexible load indicated reductions of 16.9% for cooling, 0.7% for supply fans, and 10.0% for lighting. According to previous studies, these results indicate that the LDR strategy can provide a ‘relatively strong flexibility’ service when applied in DR programs [36]. In general, when DR programs prioritize ensuring occupant comfort, the FSI often remains below 20%, and the results of this study are consistent with such findings [35]. Although only the cooling setpoint and lighting density were controlled during the DR program in this study, it is expected that the quality of demand flexibility services could be further enhanced in future studies as additional control variables are incorporated.

4.5. Electricity cost

This section evaluated the electricity cost reduction achieved by the LDR strategy. Electricity tariffs in South Korea are determined based on seasonal variations and peak load periods. Table 3 presents the electricity energy charges in South Korea by season and time period [39].

In this study, this tariff structure was applied to analyze electricity costs during the DR period, and the results are shown in Fig. 9.

The electricity cost analysis results showed that the electricity cost during the DR period under the proposed LDR strategy was 4,629 KRW, representing a reduction of approximately 8.8% compared with the

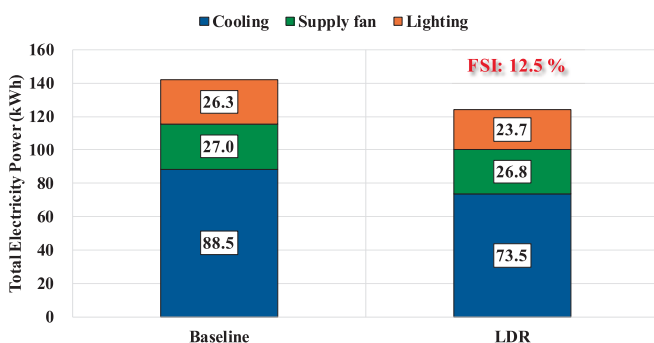


Fig. 8. Total electricity power of demand flexibility resources between baseline and LDR strategy.

Table 3

Electricity energy charge in South Korea by season and time period.

(General (A) Type 2, High-Voltage (A), Option 1) Electricity energy charge (KRW/kWh)			
Time period	Summer (Jun-Aug)	Spring & Fall (Mar-May & Sep-Oct)	Winter (Nov-Feb)
Off-peak	81.4	81.4	90.1
Mid-peak	132.6	88.8	120.5
On-peak	155.1	100.1	135.3

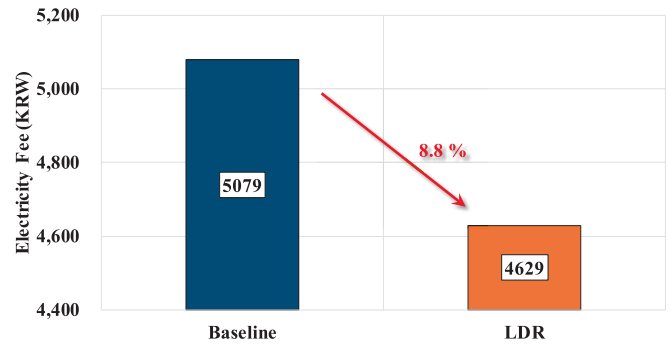


Fig. 9. Electricity fee between baseline and LDR strategy.

baseline. This reduction resulted from the decrease in electricity demand. Although additional incentives associated with DR programs were not considered in this study, greater cost savings are expected if such incentives are included in future analyses.

4.6. Performance of cooling system

This section analyzed the performance of the cooling system. Because the cooling system of the target building was an air-source heat pump, the coefficient of performance (COP) was used as the performance evaluation metric. As the case study used an EnergyPlus-based air-source heat pump model, the coefficient of performance (COP) discussed in this section represents the system's simulated performance, rather than individual device-level control actions. Fig. 10 shows the performance curves of the cooling system as a function of the part load ratio (PLR) under the baseline and LDR strategies. The green semi-transparent box indicates the PLR range of 90 to 100%. In general, DR events occur during on-peak periods, and in this study, the DR program was also implemented during the on-peak hours of a summer design day [40]. From this perspective, since the system operates under high-load conditions corresponding to the 90 to 100% PLR range during on-peak period, securing the potential to improve system performance within this range is important.

The observed COP improvement of approximately 2.1% under the

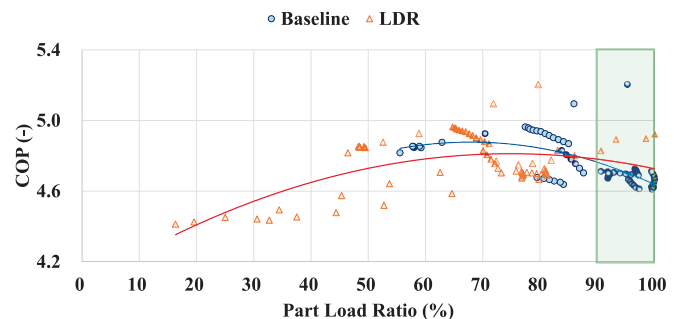


Fig. 10. Performance curves by part load ratio between baseline and LDR strategy.

LDR strategy within the 90–100% PLR range should be interpreted because of the interaction of several effects within the simulation model at system level, rather than as evidence of a single ideal-cycle mechanism. By gradually increasing the cooling setpoint, the LDR strategy reduced zone sensible cooling demand during the on-peak period, thereby alleviating instantaneous compressor loading to a slight extent compared to the baseline. Under these conditions, the cooling coil could satisfy the load with a less severe evaporating-side temperature requirement, likely reducing the effective temperature lift across the cycle. Additionally, since the heat pump model reflects temperature- and part-load dependent performance characteristics, the reported COP also encompasses the aggregated part-load behavior of the simulated system within the high PLR region. As the reduction in supply fan electricity was relatively small (0.7%), the COP gain appears to be primarily driven by cooling-side load modulation rather than fan-side effects. Therefore, the COP improvement is interpreted as resulting from load relief, modified part-load operation and reduced compressor power per unit of cooling output. Internal device-level mechanisms such as inverter modulation, compressor unloading and expansion valve optimization were not resolved independently in the present study.

5. Conclusions

This study proposed the LDR-based DR control strategy as a practical approach for implementing GEBs, aiming to secure demand flexibility while ensuring occupants' thermal and visual comfort. The effectiveness of the proposed strategy was quantitatively evaluated during summer on-peak periods. The significance of this study lies in verifying the feasibility of a practical DR strategy that can be applied in existing building control environments without relying on complex MPC or advanced optimization techniques. The main findings of this study can be summarized as follows.

- The LDR strategy stably maintained occupants' thermal comfort indices (PMV and PPD) within the comfort range during the DR period and effectively reduced the likelihood that occupants would perceive discomfort compared with the RDR strategy, which involves abrupt control changes.
- The quantitative evaluation of demand flexibility showed that the FSI of the LDR strategy during the DR period was approximately 12.5%, confirming that a 'relatively strong flexibility' level of demand flexibility service can be provided even under conditions that ensure occupant comfort.
- The grid-building interaction analysis based on GII indicated that the LDR strategy, by smoothly adjusting electricity demand, exhibited potential as a grid-interactive operational strategy required in the early stage of GEB deployment.
- The electricity cost analysis showed that the LDR strategy achieved an electricity cost reduction of approximately 8.8% compared with the baseline, which resulted from a decrease in electricity demand.
- The cooling system performance analysis showed that, in the 90–100% PLR range corresponding to the on-peak period, the LDR strategy improved COP by approximately 2.1% compared with the baseline. This trend is interpreted as a system-level consequence of reduced cooling-side load, modified part-load operation, and a likely reduction in effective temperature lift, rather than as evidence of a single isolated component-level mechanism.

Meanwhile, this study has the following limitations. The case study building does not include on-site renewable energy-based power generation systems, and therefore no electricity export to the grid occurs. Under these conditions, the quantitative results for grid interaction impact (GII) and demand flexibility (FSI) may differ if renewable generation or energy storage systems are incorporated. In particular, when export power from on-site generation exists, DR strategies can be extended beyond simple demand reduction to flexibility resources that

consider bidirectional power flows. Therefore, GII should only be interpreted in the context of an import-dominant building in the present study, and a more complete assessment of bidirectional grid interaction will require future case studies to include PV and ESS.

In addition, the quantitative results obtained in this study should be interpreted in the context of the selected case study: a U.S. DOE small office prototype that was simulated under summer on-peak conditions in Daejeon, South Korea. Therefore, the reported values of FSI, GII, electricity cost reduction and COP improvement may vary depending on building type, climatic conditions, occupancy patterns and HVAC system configurations. Nevertheless, the proposed LDR-based DR framework could be useful in other contexts, provided further case-specific calibration and validation are performed.

Furthermore, this study focused on a summer on-peak case study and did not implement a seasonal tuning procedure based on historical data. In practical applications, the proposed strategy could be recalibrated seasonally using BAS or BEMS historical data such as past load profiles, indoor temperature responses, occupancy schedules, local weather conditions and seasonal tariff structures. Accordingly, the seasonal adaptation of the proposed strategy should be considered an important area for future research.

A direct simulation-based comparison with MPC was beyond the scope of this study. However, benchmarking under identical case-study conditions would provide valuable insight into the trade-off between optimal control and practical implementability.

Future studies will quantitatively analyze changes in demand flexibility and grid impact by considering export power in building models that include distributed energy resources such as PV systems and ESS. Through this approach, the LDR strategy proposed in this study will be generalized to more advanced GEB environments, and its applicability under diverse grid conditions will be further validated.

CRedit authorship contribution statement

Dong Eun Jung: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Byeongmo Seo:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Haneul Choi:** Writing – review & editing, Conceptualization. **Gwangwoo Han:** Writing – review & editing, Methodology, Conceptualization. **San Jin:** Writing – review & editing, Conceptualization. **Donghun Kim:** Writing – review & editing, Conceptualization. **Sung-yong Son:** Writing – review & editing, Conceptualization. **Jonghun Kim:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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