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White-Model Predictive Control for Balancing Energy Savings and Thermal Comfort

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Abstract: To save energy consumed by a building, utilizing optimal predictive control with model predictive control (MPC) makes the most of energy storage systems (ESSs) to reduce the electrical energy consumption of peak and heavy loads. This study evaluated MPC applicability in a multi-zone commercial building using the EnergyPlus model and conducted multi-objective optimization of thermal comfort and energy savings. As a result of the simulation, optimal ESS charging scenarios responded to the fluctuating electricity pricing system, and changing the peak load time reduced the electricity bill of the grid by 55% compared to the existing operating method. At the same time, room temperatures stayed within the thermal comfort range, and the Pareto curve showed a proper balance between energy saving and thermal comfort. Especially, the proposed method with a white model is applicable for MPC applications in commercial buildings, as it gave optimal solutions within the target time interval.

Keywords: model predictive control; multi-objective optimization; genetic algorithm; thermal comfort; energy saving

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1. Introduction

According to the Department of Energy (DOE US), extensive study is required to improve the energy efficiency of a building since it accounts for 70% of electricity consumption [1]. Moreover, since heating, ventilation, and air-conditioning (HVAC) systems consume more than 30% of an entire building's energy usage, effective control of the HVAC system can reduce the energy consumption of the building. In this regard, model predictive control (MPC) and relevant studies that establish control strategies using the latest model are constantly increasing [2]. As many countries use electricity pricing systems that charge different electricity pricings at different times, such as time of use (TOU), on-off-peak pricing (OPP), and real-time pricing (RTP), MPC studies are being increasingly conducted. Since the MPC study is undertaken to minimize objective functions through the model that predicts the building's load, a model for precise demand prediction is critical in applying MPC effectively. The models for MPC are classified as the white-box, black-box, and gray-box models. According to previous studies, most studies use the gray-box or black-box model for MPC because it is better for computation speed [2].

The most widely used gray-box model is the resistance and capacitance (RC) model. The RC model calculates a building's load by organizing the physical relation of the building as a linear equation, which leads to reduced calculation time. Therefore, it is helpful for predictive control [3–6]. The black-box model is a model that deals with the input and output data secured from the operational data of the building. However, expert knowledge is not required to establish the load model of the building. Black-box models such as artificial neural network (ANN) and deep learning models are being widely used [7–9]. However, the black-box model requires long-term data collection for learning, and the model's performance depends on the quality of the data. The white-box model includes building energy simulation (BES) programs such as EnergyPlus, TRNSYS, and Modelica. It is possible to describe a building with more details in white-box models than the gray-box and black-box models because BES program models target systems in detail and describe the physical relationships among parameters, as well as input and output information, to calculate the thermal behavior of the building. However, some related calculation parameters slow down the calculation speed, and it is not easy to interconnect optimization tools and BES programs. Therefore, the white-box model (with the applicable technology such as parameter optimization) is commonly used for system sizing in the design phase [2].

Since the computational calculation speed has been constantly improving, with the middleware development interconnecting the BES programs with optimization tools, MPC studies with the white-box model are being conducted. The building control virtual test bed (BCVTB), developed by Lawrence Berkeley National Laboratory, is one of the commonly used middleware programs that utilizes white-box models such as Energyplus, TRNSYS, and ESP-r as the building and system model. BCVTB also uses a control model in Modelica or facilitates co-simulation for control via directly programmed MATLAB and Python code [10]. For example, Nouvel and Alessi conducted an indoor thermal comfort control study using co-simulation of EnergyPlus and MATLAB [11]. Rackes and Warning conducted a multi-purpose optimization study considering energy saving and indoor air quality [12]. Aside from these, many optimization studies based on the white-box model have been performed [12–15]. The results of preceding research are listed in Table 1.

Table 1. Preceding model predictive control (MPC) research and investigations according to existing building models in the literature.

Authors	Building Model	PV [1]	ESS [2]	Obj1 [3]	Obj2 [4]	Controlled Zones
Roberto et al. (2008) [3]	RC	×	×	energy saving	-	single zone
Chen et al. (2015) [4]	RC	×	×	energy saving	thermal comfort	single zone
Mbungu et al. (2016) [5]	RC	×	×	energy saving	-	unknown
Jeon and Kim (2020) [7]	deep learning	○	×	energy saving	-	single zone
Mohammad and Fariborz (2021) [8]	deep learning	×	×	energy saving	thermal comfort	5 zones
Pinto et al. (2021) [9]	deep learning	○	○	energy saving	-	4 buildings
Nouvel et al. (2012) [11]	EnergyPlus	×	×	thermal comfort	-	single zone
Rackes and Waring (2014) [12]	EnergyPlus	×	×	energy saving	indoor air quality	single zone
Zhao et al. (2015) [13]	TRNSYS	○	○	energy saving	-	one building
Li and Malkawi (2016) [14]	EnergyPlus	×	×	energy saving	thermal comfort	single zone
Jorissen et al. (2019) [15]	Dymola	×	×	energy saving	-	9 zones

[1] Photovoltaic; [2] energy storage system; [3] object 1; [4] object 2.

According to Reynolds et al., it is impossible to use white-box models with advanced metaheuristic optimization strategies in most scenarios targeting operational optimization [16]. Even though optimal energy control requires many repeated simulations, there is not enough time to apply to MPC operation strategy because it requires constant updates in the using phase. Moreover, the preceding optimization study based on the white-box model was just a simple building energy model or was focused on a single zone with few control parameters [16]. However, it is possible to consider the effect of various control variables while monitoring the behavior of the entire system because most white-box models describe the target system in detail. In addition, with proper fitting, the white-box model is expected to follow actual use data similar to the gray-box model and black-box model. Lastly, the white-box model has an advantage because it is commonly used for the design phase, so the development model can be utilized while designing [2].

In this regard, Li and Malkawi's study found that there has been no research that considered energy cost saving and thermal comfort at the same time while using the white-box model and optimal control tools, a study which they further carried out using an MPC [14]. Energy saving and thermal comfort have an adversarial relationship, and it is crucial to find an optimal balance between them. However, many studies consider a single-objective optimization. In the current study, to apply a practical MPC to a commercial building, MPC research using multi-objective optimization tools with the white-box model applicable to the multi-zones with more control parameters was conducted. Primarily, it focused on the photovoltaic (PV) system that significantly increased MPC effects, with a proper control method of energy storage system (ESS) in TOU environment. Although many studies point out that simulation time is a problem in MPC research based on the white-box model, it is difficult to find studies that compare central processing unit (CPU) time with MPC performance. Therefore, in this study, a practicality analysis of an MPC study based on the white-box was conducted in which the MPC framework and CPU time were considered.

2. Target Simulation Models

In this study, ShopWithPV and Storage.idf, an example building model provided by EnergyPlus, was selected as a reference model for the study. The example building is a common commercial building that includes a PV power system and ESS system capable of storing energy. Latitude and longitude (37.4° N, 126.6° E) and the weather.epw file of Incheon were used for location information of the building. It is a commercial building with 390 m^2 of floor area and has five air conditioning zones, and the set temperature of each zone is 24 °C. The office hours of the five air conditioning zones are 09:00 to 18:00 h, and lighting fixtures and electric appliances suitable for the air conditioning zones are changed according to the schedule. The major parameters for each zone are listed in Table 2. The relevant information of the PV system and ESS system is provided in Tables 3 and 4, respectively. The thermal comfort of the target building met ASHRAE 90.1 (2004) [17] standards, and the detailed material property of the building and the performance of new and renewable energy facilities can be found in documents provided by EnergyPlus [18].

Table 2. Parameters of the reference building models.

Parameter	Zone-1	Zone-2	Zone-3	Zone-4	Zone-5
Floor area (m^2)	78.6	61.1	78.6	61.1	111.1
Ceiling height (m)	5	5	5	5	5
Cooling set point (°C)	24	24	24	24	24
Light (W)	1178.0	916.1	1178.0	916.1	1664.2
Equipment (W)	465.9	362.3	465.9	362.3	658.2
Office hours (h)	9 to 18	9 to 18	9 to 18	9 to 18	9 to 18

Table 3. Parameters of reference PV models.

Parameters		Parameters	
Rated electric power output	39 kW	Radiative fraction	0.25
Nominal voltage input	368 V	Rated maximum continuous output power	14 kW
Efficiency at 10% power and nominal voltage	0.839	Efficiency at 100% power and nominal voltage	0.93

Table 4. Parameters of reference ESS models.

Parameters		Parameters	
Schedule	Always on	Maximum storage capacity	100,000 MJ
Efficiency for charging	0.85	Maximum power for discharging	50 kW
Discharging energetic efficiency	0.7	Maximum power for charging	25 kW

Figure 1 is a simple sequential diagram of the target building system, including PV and ESS, and it shows how the target building manages the required electrical energy demand.

The electricity demand of the building is calculated over time, and the electricity generated by the PV module at a corresponding time is consumed first. The surplus power from the PV module is stored in ESS, and it is used if PV cannot meet the electricity demand later on. In contrast, power from the grid is used when the electricity from PV and ESS could not meet the building's load. Depending on electricity rates and operating strategies, ESS charging from the grid is required. Even though the power generated from PV should be calculated based on the predicted insolation at the applicable phase, it is assumed that the insolation is precisely expected because the accuracy of the insolation has been confirmed in prior studies, one of which was conducted from the perspective of system control [19]. MPC simulation was conducted from 15 August to 17 for the summer peak load.

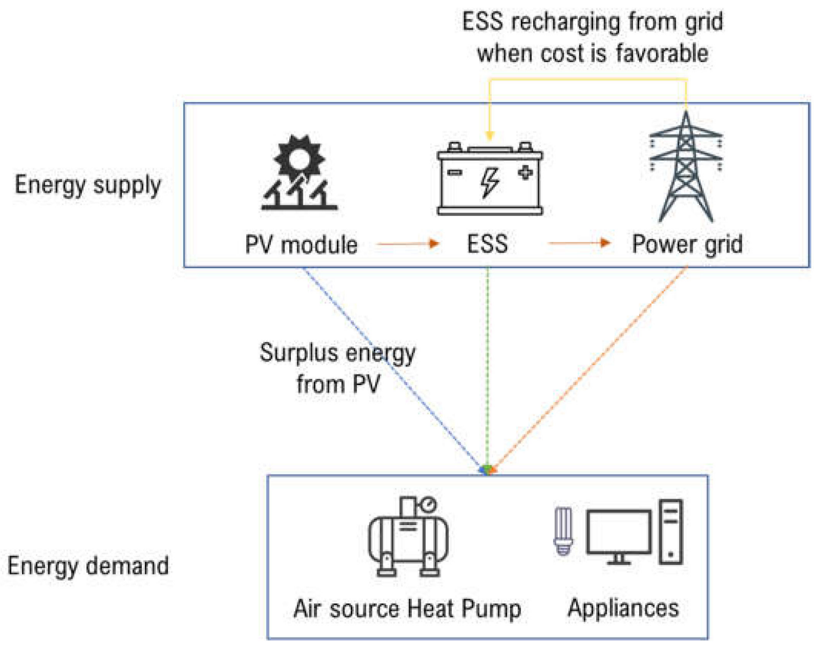

Figure 1. Target building and energy system diagram.

3. Multi-Objective Optimal Control Strategy

3.1. Genetic Algorithm

Various optimal control algorithms are applied to the study of building's optimal control [20–22]. No optimization algorithm has provided the best solution to every problem until now. Each optimization algorithm has its positive and negative aspects owing to the differences in deducing the optimal solution. Therefore, users should choose an optimal solution based on its purpose and optimization problems. This study used the multi-objective genetic algorithm (GA), which converts possible solution sets into integer vectors and conducts a selection, reproduction, mutation, and fitness evaluation to describe the evolution process of natural selection. This natural selection process is repeated until the last good solution survives, which is then selected as a final answer [23]. The GA algorithm has been applied to studies for optimal control of the building because it is advantageous for the nonlinear property of the building [24]. The current study also uses the GA algorithm for optimal control. The detailed optimization process of the GA algorithm is found in the references [25]. The primary parameter settings of the genetic algorithm are provided in Table 5. The greater population size and the value of maximum generation implies a possibility of a solution closer to the optimal solution. However, if the values of two parameters are increased substantially, it becomes similar to calculating almost any number of cases, which increases the time and cost of the simulation. Therefore, a user should enter proper setting values based on their experience. This study uses default values suggested by the MATLAB documentation [26]. 'Max time' means the maximum time spent on optimization simulation, and the current study limits maximum time to one hour and considers the MPC's characteristic planning for the next day or undertakes real-time control on the previous day at 23:00 h. However, additional simulations were conducted for three hours on unlimited cases to analyze the accuracy of the one-hour case, considering that more time in the optimization simulations results in better accuracy.

Table 5. Parameters used for genetic algorithm (GA).

Parameter	Settings Used
Population size	20
Maximum generation	200 × number of variables
Maximum time	1 h, 3 h, unlimited

3.2. Coupling EnergyPlus and MATLAB

This study used EnergyPlus, a detailed analysis program, as a model of MPC, and a genetic algorithm that uses the GA multi-objective function was provided by MATLAB. The EnergyPlus Simulation toolbox provided by MATLAB and an external interface feature of EnergyPlus was used for the data communication between two programs [26,27]. However, EnergyPlus does not allow transmission and receiving of the data for all physical parameters in EnergyPlus, so the EnergyPlus model for this study was not allowed to operate ESS from the outside through an external interface. Without access from the outside, EnergyPlus is able to assign ESS charging schedules over time via the energy management system (EMS), but in this case, it was difficult to use an advanced control algorithm such as a multi-objective genetic algorithm. Therefore, in this study, ESS status was calculated using a simple multiplying operation according to the charging efficiency of the target ESS model (Equation (1)). The charging efficiency was 85%.

$$\mathrm{ESS}_{\mathrm{charge,t}} = \mathrm{E}_{\mathrm{grid,t}} \times 0.85 \tag{1}$$

where $\mathrm{ESS}_{\mathrm{charge,t}}$ is the energy flow of the charging of battery over time t (kWh), and $\mathrm{E}_{\mathrm{grid,t}}$ is the energy flow of the utility grid over time t (kWh).

3.3. Objective Function

This study considers two criteria for optimization, which include maintaining thermal comfort while minimizing the cost of electricity. The first objective function was to build a set temperature operation plan for a day, which keeps the indoor temperature of each zone at approximately 24 °C, which is the set temperature of the reference model. Therefore, if the indoor temperatures of the five zones were lower or higher than 24 °C during office hours (from 09:00 to 18:00), a penalty was calculated according to Equation (2). The set temperature range, which is an optimal control variable, ranged from 21 °C to 26 °C. The control was undertaken only during office hours, i.e., from 09:00 to 18:00.

$$\min f_{\mathrm{obj1}} = \sum_{t=9}^{18} \sqrt{\left(24 - T_{\mathrm{in,t,zone}}\right)^2} \tag{2}$$

where $\min f_{\mathrm{obj1}}$ is the first objective function related to thermal comfort, and $T_{\mathrm{in,t}}$ is the indoor temperature over time t (°C).

The second objective function was to minimize the electricity cost of the building, which is represented as Equation (3). The control parameter is the amount of electricity used to charge ESS. Table 6 demonstrates the domestic TOU rate system of commercial buildings. The charging time was set from 01:00 to 08:00, which falls under a light load due to the cheap electricity rate [28].

$$\min f_{\mathrm{obj2}} = \sum_{t=1}^{24} \mathrm{E}_{\mathrm{grid,t}} \times \mathrm{TOU}_{\mathrm{t}}$$

$$\text{here, } E_{grid,t} = ESS_{charge,t} + E_{consumption,t} - (E_{PV,t} + ESS_{discharge,t}) \quad (3)$$

where minf_{obj2} is the second objective function where the cost of electricity should be minimized; $E_{consumption,t}$ is the energy consumption over time t (kWh); $E_{PV,t}$ is the energy flow of the PV (kWh).

Table 6. Time of use (TOU) energy tariff.

	Light Load	Middle Load	Heavy Load
Time	23:00–9:00	09:01–10:00 12:01–13:00 17:01–23:00	10:01–12:00 13:01–17:00
Tariff ($/kW)	0.05	0.13	0.21

Equation (3) is related to the usage sequence of energy from PV and ESS. As mentioned in the introduction, the reference model in each time step uses the electricity generated by PV first, and if there is surplus electricity, it is stored in ESS and used for the next time step. The electricity from the grid is used when the building's electricity demand exceeds PV generation. The optimal control case in the GA algorithm also uses PV generation first and stores surplus electricity. However, the starting time of using the electricity stored in ESS is set after 09:00, the time when the light load is finished and the middle load starts, in consideration of charging efficiency.

Finally, the MPC simulation outputs the building operation schedule, minimizing Equations (1) and (2) simultaneously. Major setting values of the two control parameters are listed in Table 7. Avoiding frequent control parameter settings and considering calculation time for the optimization, the optimization was undertaken to calculate the time unit control variable. Because this study controlled all five zones for 10 h of operating time, a total of 50 variables were generated; one ESS contained 8 h of charging schedule during the night, and one simulation decided 58 optimal control variables.

Table 7. Bounds of the GA parameters to be optimized.

Variable	Time	Number of Variables	Lower Bound	Upper Bound
Set point (Five zones)	07:00–18:00	50 (10 h × 5 zones)	21 °C	26 °C
ESS charge	01:00–08:00	8	0 kW	25 kW

The optimization performance was evaluated along with the time spent on the simulation to investigate MPC usability of the white-box model for the commercial building. The time spent on the simulation largely depended on the user's computer specifications. This study used a computer with an Intel i9-9940X @ 3.30 GHz CPU and 128 GB memory. The graphics card was not used for the calculation. The optimization framework of this study is shown in Figure 2.

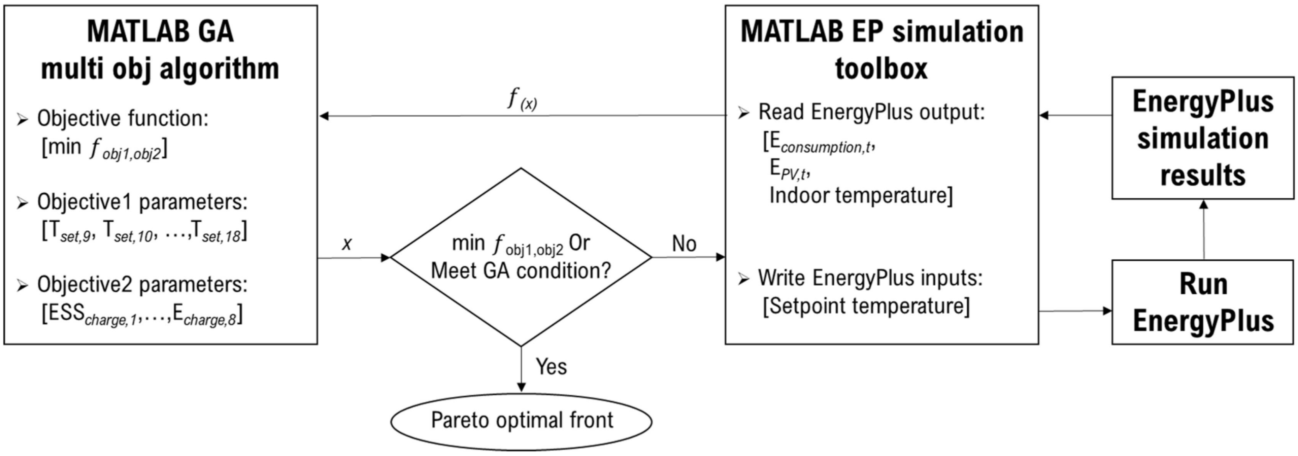

Figure 2. Proposed MPC scheduling algorithm optimized by GA.

4. Optimization Results

Figure 3 shows the indoor temperature fluctuation of five zones during the test period over time while conducting the optimization simulation for an hour. It was found that the indoor temperatures of every zone stayed within the thermal comfort zone. Even though the temperature of zone 2 deviated from that of the thermal comfort zone set initially on 17 August at 17:00, it was 21.83 °C, which is not very different from that in the comfort zone. This is due to the physical response delay effect, which means the zone's set temperature is not always the same as the real response temperature. This difference can be removed by setting indoor temperature boundaries as a limiting condition or giving weighted value to the indoor thermal comfort objective function, as in previous studies [14]. Control is undertaken toward the dynamic change of indoor temperature from 09:00 to 18:00 (Figure 3).

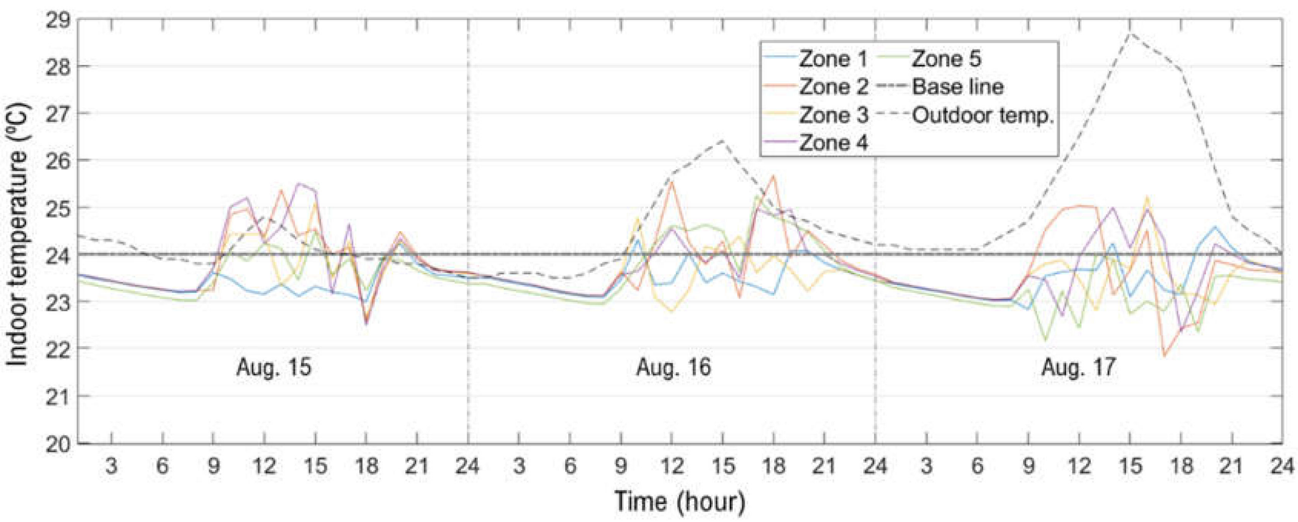

Figure 3. Comparison of optimized indoor operating temperatures.

Figure 4 shows the behavior of the electricity grid usage. The optimal control used the scenario that charges the ESS during the night when the electricity cost is low and uses charged energy during the heavy load period to shift the peak load when the electricity cost is expensive. In particular, it secured more electricity during the night on 15 and 16 August when the PV generated less energy, and it charged less electricity on 17 August when the PV generated more energy. However, it is confirmed that ESS was charged before the system operating time and PV generation. Electricity from the grid was not used, and for the heavy load, 100% of the electricity was used from the ESS and PV generation, which was different from the time when the temperature was set at 24 °C; further, ESS state of charge decreased upon starting the operation every day (Figure 4).

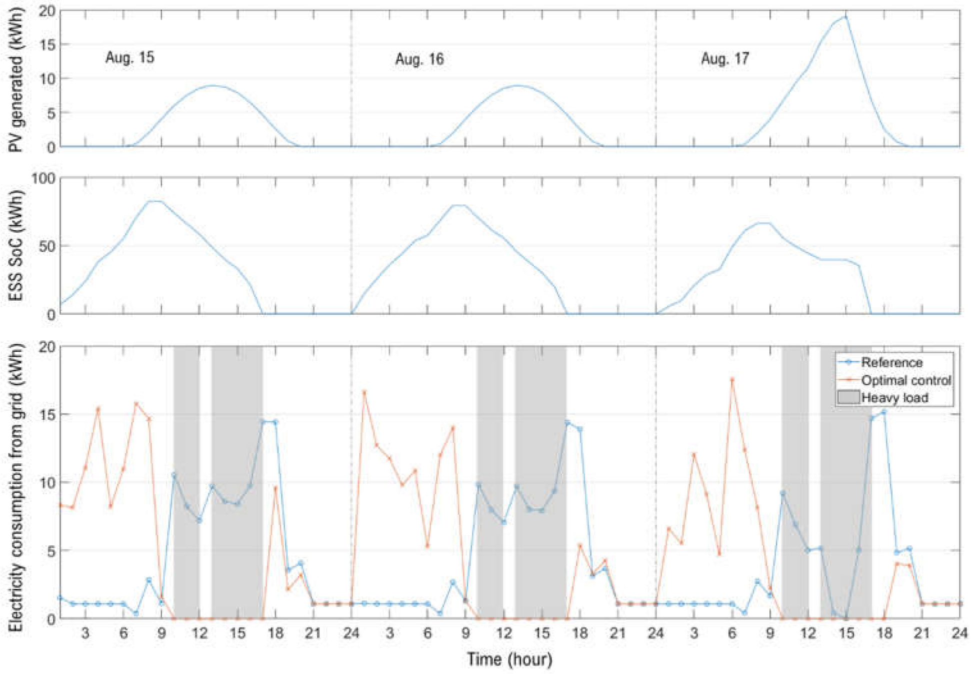

Figure 4. Optimized ESS variation (middle) and grid electricity consumption (bottom).

Figure 5 shows the electricity consumption from the grid and cost of the reference model and the optimal control. The suggested operating scenario reduced the electricity cost by 60% on 15 and 16 August when the PV generated less electricity, and it reduced the electricity cost by 55% on 17 August when the PV generated more electricity as the electricity from the PV fulfilled the electricity demand of the building. The two cases showed a similar grid energy consumption for three days while the simulation was undertaken. On 16 and 17 August, even though the optimal control model consumed more electricity from the grid, the electricity cost was considerably reduced with a proper operating scenario using the ESS. In other words, although the total electricity consumptions were similar due to the same PV generation and the load of the same building, the electricity cost was considerably reduced with appropriate operational management.

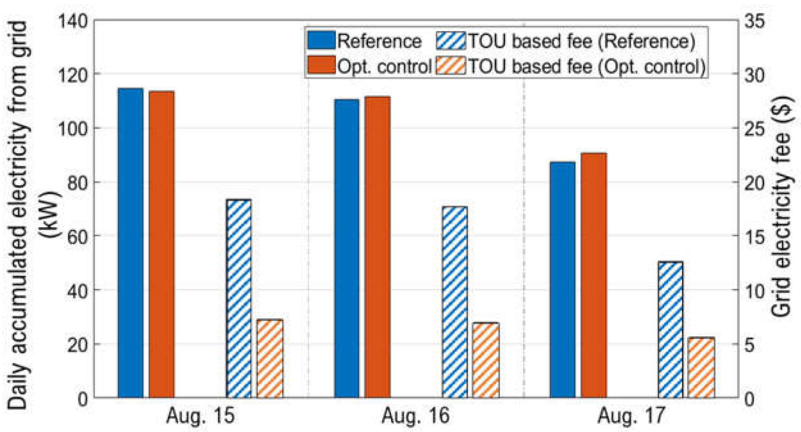

Figure 5. Comparison of grid energy consumption and cost of electricity.

As a result, the multi-objective optimization simulation with the EnergyPlus model maintained the thermal comfort of multi-zones while reducing the building's peak load migration and electricity cost. In particular, the limitation of the optimization time by one hour was because the operating plan was to proceed on the previous day for typical MPC data communication; this optimal control of a commercial building based on a detailed analysis program can be used as a reference test case in terms of usability at the real-world MPC application step.

Mostly, the optimization simulation was closer to the optimal solution when there was more time for the simulation. Figure 6 shows the time spent for the optimization simulation (i.e., 1 h, 3 h, and unlimited) and compares them with the results. The thermal comfort was calculated by Equation (1) and was closer to zero, meaning that the set temperatures of five zones were similar to 24 °C. On 17 August, the ideal simulation result was produced as it showed that when the optimization consumed more time, it met the thermal comfort and reduced the electricity cost. However, on 15 and 16 August, the thermal comfort scores were lower in the 1-h case, while having the lowest electricity fee. The optimization was undertaken toward securing the balance of two objective functions, so the unlimited cases showed slightly better optimization results during those three days compared to the other cases. However, the results were similar, particularly in terms of energy fee. In other words, the unlimited case consumed ~8 h of CPU time on average during those three days. Considering the characteristics of the MPC, which was conducted on the previous day at 23:00 or in real-time, the 1-h model obtained field applicability and provided similar results to the 3 h and unlimited models.

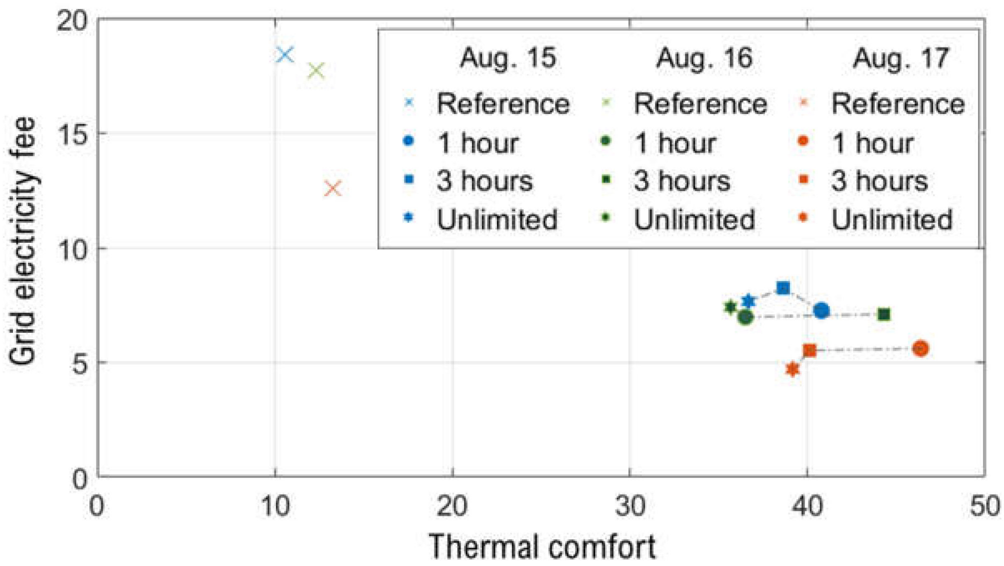

Figure 6. Pareto curve for MPC control in a commercial building.

Obj 1 is a value produced by adding all scores of the five zones for the control, so each zone's indoor temperatures need to be analyzed. Figure 7 shows the indoor temperatures of each zone with a boxplot according to the time spent on the optimization. The medians were between 23 °C and 24 °C in all of the simulations (Figure 7). Most of the maximum and minimum values were between 22 °C and 26 °C, which are within the comfort range of this study (except for one point in zone 2, in the 1-h simulation case on 18 August). However, considering the similar cost optimization results, cases with more optimization time showed more minor differences in indoor temperatures. The overall simulation results of this study are summarized in Table 8.

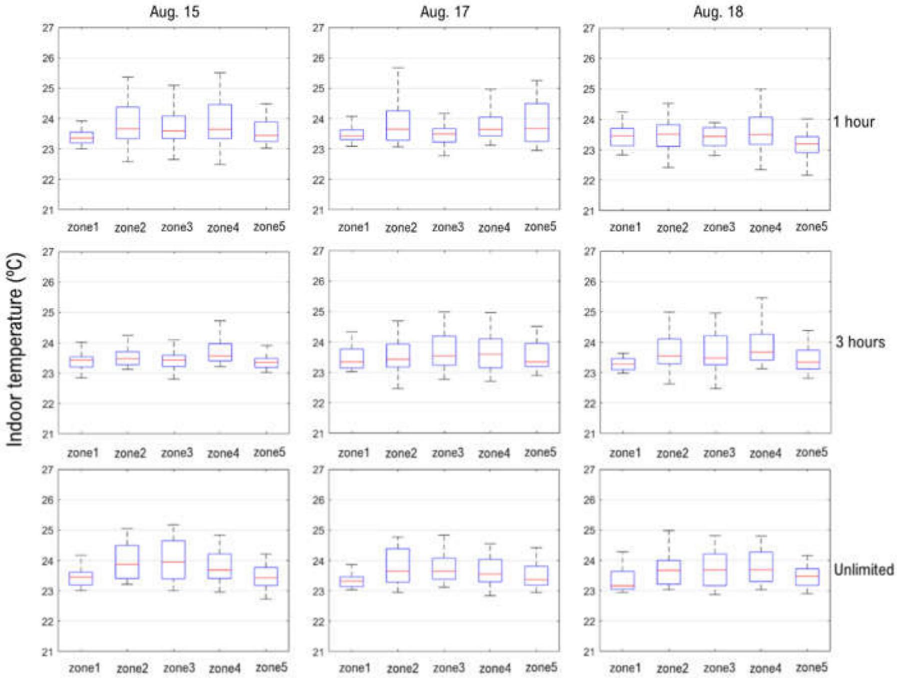

Figure 7. Indoor temperatures depending on test case scenarios.

Table 8. MPC results of the target building.

Day	Cases	Grid Power Usage (kW)	Grid Electricity Price ($)	Saving Cost Rate (%)	$\min f_{obj1}$	CPU Time (min)
15 August	Reference	114.6	18.4	-	10.5	-
	Opt. 1 h	113.5	7.2	60.5	40.7	60
	Opt. 3 h	129.4	8.2	55.3	38.6	180
	Opt. Inf	114.9	7.6	58.3	36.6	485
16 August	Reference	110.3	17.7	-	12.3	-
	Opt. 1 h	111.5	6.9	60.5	36.5	60
	Opt. 3 h	116.2	7.1	59.8	44.3	180
	Opt. Inf	14.3	.4	58.1	35.6	556
17 August	Reference	7.3	2.6	-	13.2	-
	Opt. 1 h	0.5	5.6	55.5	46.3	60
	Opt. 3 h	1.4	7.0	56.1	40.1	180
	Opt. Inf	91.2	4.7	62.6	39.1	501

5. Conclusions

This study suggests a framework for conducting an MPC simulation to reduce the electricity fee while maintaining thermal comfort in a commercial building. The study directly applied an optimization algorithm to a physical building energy simulation model rather than using a model in an existing gray-box or black-box model. The white-box model was not used for the MPC model because it requires too much time for optimization. This study conducted additional analysis for the time spent on optimization to investigate the field application possibility of the MPC based on the white-box model at the usage phase.

The target building was a typical commercial building consisting of five zones. The optimization results were analyzed with more control parameters than a single zone-based building. This study optimized the MPC energy model applicable to real-world commercial buildings by adding the PV and ESS. As a result of the simulation for the multi-objective optimization on the thermal comfort and energy savings, it was found that the suggested framework with one hour of CPU time (considering the actual MPC operating interval) can reduce the electricity fee by more than 55% under the current TOU electricity rate system, while maintaining thermal comfort, compared to the model without the optimal control. These results were similar to cases where increasing time was spent on the simulation to obtain the optimal solution. Since the results of this study were obtained by analyzing specific CPU times and MPC performance simultaneously, it can be used as a reference case study for white-box model-based MPC studies of commercial buildings. This study is expected to provide meaningful application to zones requiring different thermal comfort levels, which is different from existing MPC-based studies that focus on single-zone analysis.

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References

1. Doe, U. *Buildings Energy Data Book*; Energy Efficiency & Renewable Energy Department: Washington, DC, USA, 2011.
2. Drgoňa, J.; Arroyo, J.; Cupeiro Figueroa, I.C.; Blum, D.; Arendt, K.; Kim, D.; Ollé, E.P.; Oravec, J.; Wetter, M.; Vrabie, D.L.; et al. All You Need to Know About Model Predictive Control for Buildings. *Annu. Rev. Control.* **2020**, *50*, 190–232. [CrossRef]
3. Freire, R.Z.; Oliveira, G.H.C.; Mendes, N. Predictive Controllers for Thermal Comfort Optimization and Energy Savings. *Energy Build.* **2008**, *40*, 1353–1365. [CrossRef]
4. Chen, X.; Wang, Q.; Srebric, J. Model Predictive Control for Indoor Thermal Comfort and Energy Optimization Using Occupant Feedback. *Energy Build.* **2015**, *102*, 357–369. [CrossRef]
5. Mbungu, N.T.; Naidoo, R.M.; Bansal, R.C. Real-Time Electricity Pricing: TOU-MPC Based Energy Management for Commercial Buildings. *Energy Procedia* **2017**, *105*, 3419–3424. [CrossRef]
6. Jeon, B.K.; Kim, E.J.; Shin, Y.; Lee, K.H. Learning-Based Predictive Building Energy Model Using Weather Forecasts for Optimal Control of Domestic Energy Systems. *Sustainability* **2019**, *11*, 147. [CrossRef]
7. Jeon, B.K.; Kim, E.J. LSTM-Based Model Predictive Control for Optimal Temperature Set-Point Planning. *Sustainability* **2021**, *13*, 894. [CrossRef]
8. Esrafilian-Najafabadi, M.; Haghighat, F. Occupancy-Based HVAC Control Using Deep Learning Algorithms for Estimating Online Preconditioning Time in Residential Buildings. *Energy Build.* **2021**, *252*, 111377. [CrossRef]
9. Pinto, G.; Deltetto, D.; Capozzoli, A. Data-Driven District Energy Management with Surrogate Models and Deep Reinforcement Learning. *Appl. Energy* **2021**, *304*, 117642. [CrossRef]
10. Wetter, M. Co-Simulation of Building Energy and Control Systems with the Building Controls Virtual Test Bed. *J. Build. Perform. Simul.* **2011**, *4*, 185–203. [CrossRef]
11. Nouvel, R.; Alessi, F. A Novel Personalized Thermal Comfort Control, Responding to User Sensation Feedbacks. *Build. Simul.* **2012**, *5*, 191–202. [CrossRef]
12. Rackes, A.; Waring, M.S. Using Multi-Objective Optimizations to Discover Dynamic Building Ventilation Strategies That Can Improve Indoor Air Quality and Reduce Energy Use. *Energy Build.* **2014**, *75*, 272–280. [CrossRef]
13. Zhao, Y.; Lu, Y.; Yan, C.; Wang, S. MPC-Based Optimal Scheduling of Grid-Connected Low Energy Buildings with Thermal Energy Storages. *Energy Build.* **2015**, *86*, 415–426. [CrossRef]
14. Li, X.; Malkawi, A. Multi-Objective Optimization for Thermal Mass Model Predictive Control in Small and Medium Size Commercial Buildings Under Summer Weather Conditions. *Energy* **2016**, *112*, 1194–1206. [CrossRef]
15. Jorissen, F.; Helsen, L. Integrated Modelica Model and Model Predictive Control of a Terraced House Using IDEAS. In *Org/Events/Modelica2019/Subpages/Modelica-Conference-2019-Proceedings*; Linköping University Electronic Press: Linköping, Sweden, 2018.

16. Reynolds, J.; Rezgui, Y.; Kwan, A.; Piriou, S. A Zone-Level, Building Energy Optimisation Combining an Artificial Neural Network, a Genetic Algorithm, and Model Predictive Control. *Energy* **2018**, *151*, 729–739. [CrossRef]
17. Standard 90.1-2004. *Energy Standard for Buildings Except Low-Rise Residential Buildings*; Standard, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.: Atlanta, GA, USA, 2004; p. 176.
18. Documentation, E. The Reference to EnergyPlus Calculation. *Eng. Ref. Energyplus* **2019**, *9*, 2.
19. Jeon, B.K.; Kim, E.J. Next-Day Prediction of Hourly Solar Irradiance Using Local Weather Forecasts and LSTM Trained with Non-Local Data. *Energies* **2020**, *13*, 5258. [CrossRef]
20. Yang, R.; Wang, L. Multi-Zone Building Energy Management Using Intelligent Control and Optimization. *Sustain. Cities Soc.* **2013**, *6*, 16–21. [CrossRef]
21. Lee, K.P.; Cheng, T.A. A Simulation–Optimization Approach for Energy Efficiency of Chilled Water System. *Energy Build.* **2012**, *54*, 290–296. [CrossRef]
22. Baños, R.; Manzano-Agugliaro, F.; Montoya, F.G.; Gil, C.; Alcayde, A.; Gómez, J. Optimization Methods Applied to Renewable and Sustainable Energy: A Review. *Renew. Sustain. Energ. Rev.* **2011**, *15*, 1753–1766. [CrossRef]
23. Mirjalili, S. Genetic Algorithm. In *Studies in Computational Intelligence*; Springer: Cham, Switzerland, 2019; pp. 43–55.
24. Reynolds, J.; Hippolyte, J.L.; Rezgui, Y. A Smart Heating Set Point Scheduler Using an Artificial Neural Network and Genetic Algorithm. In Proceedings of the International Conference on Engineering, Technology, and Innovation (ICE/ITMC), Madeira Island, Portugal, 27–29 June 2017; pp. 704–710.
25. Mathew, T.V. *Genetic Algorithm. Report Submitted at IIT Bombay*; Indian Institute of Technology (IIT): Mumbai, India, 2012.
26. MathWorks Inc. *MATLAB Documentation, MathWorks*; MathWorks Inc.: Natick, MA, USA, 2018.
27. Guide, A. *Guide for Using EnergyPlus with External Interface(s)*; United States Department of Energy: Washington, DC, USA, 2011.
28. Korea Meteorological Administration. Available online: http://home.kepco.co.kr/ (accessed on 10 February 2022).