Model predictive control of a building energy system including thermal energy storage

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Abstract

The present paper aims to verify the effectiveness of a model predictive control (MPC) strategy for an office building subject to an occupancy disturbance and time-varying electricity pricing by comparison with the conventional rule-based control (RBC) strategy. The energy system of the building includes an air-cooled chiller, stratified thermal energy storage (TES) system, two fan coil units, three heat exchangers, and five pumps. The chiller and TES operation were optimally determined by manipulating the mass flow rate of five pumps to minimize the operation cost. In order to construct reliable but computationally light prediction models, an artificial neural network (ANN) was utilized and the epsilon constrained differential evolution with a random jumping (ϵ DE-RJ) algorithm was employed for solving an optimization problem. The simulation was performed for four days in the cooling season with a discrete prediction time horizon of 24 h and control time horizon at 1-h intervals. As a result, the MPC could save approximately 8.3% in terms of the total operation cost in comparison to the RBC, which prioritizes the TES operation to manage the thermal load.

Introduction

The building sector, including both residential and non-residential buildings, accounts for approximately 20–40% of the total primary energy consumption globally (Pérez-Lombard, Ortiz, and Pout, 2008). Specifically, heating ventilation and air-conditioning (HVAC) systems are a major factor in the total energy consumption of the building sector (Energy Information Administration (EIA), 2012; International Energy Agency (IEA), 2012). For this reason, building energy systems need to be managed effectively, and recently, model predictive control (MPC) has received significant attention as an optimal control strategy for building energy systems (Afram and Janabi-Sharifi, 2014; Serale, Fiorentini, Capozzoli, Bernardini, and Bemporad, 2018).

MPC is a promising optimal control method for HVAC systems because it determines the optimal control input by solving an optimization problem in an iterative manner based on the predicted future behavior of the HVAC system (Killian and Kozek, 2016). Because of MPC's predictive nature, its utilization is ideal for controlling on-site energy storage systems (Prívará et al., 2013).

Energy storage systems that shift on-peak loads to off-peak hours, such as thermal energy storage (TES) systems, are known to improve the cost-effectiveness of HVAC operations.

Although several studies have already proposed improved control strategies for TES systems (Akbari and Sezgen, 1992; Henze, Dodier, and Krarti, 1997), it has been found that more advanced strategies such as MPC are more efficient in optimal building operations that have a TES system incorporated. For example, Halvgaard et al. (2012) applied the MPC scheme to manage a storage tank in balance with a solar collector fluctuating energy source. They found that application of MPC resulted in annual operating cost savings of 25–30%. Additionally, D'Ettorre et al. (2019) showed that adopting MPC with an HVAC system that incorporates a TES component can optimize and reduce the operation cost of a building energy system by up to 8%.

In a previous publication (Serale et al., 2018), the authors stated that one of the advantages of MPC strategy is that it can consider future disturbances on the basis of its predictive nature and optimization process. They classified the disturbances that affect MPC implementation for building energy management into three categories: climatic disturbances, occupant-behavior related disturbances, and time-variant electricity pricing disturbances. These three elements are key factors that need to be considered during the operation phase of a building energy systems, and MPC's predictive process allows for this. However, currently there is a lack of literature examining MPC's ability to manage unexpected operational disturbances.

Therefore, the purpose of this study is to investigate the MPC strategy and verify its effectiveness for optimal operation of building energy systems that incorporate a TES system. A case study was conducted to confirm MPC's ability to explore future disturbance scenarios subject to time-varying occupancy profiles and electricity prices. Considering the intrinsic nature of MPC's problem solving process, involving iterative optimization calculations, reducing the computation time of prediction while maintaining accuracy is a critical issue. Therefore, we utilized an artificial neural network (ANN) as a prediction model. Furthermore, epsilon constrained differential evolution with random jumping (ϵ DE-RJ) was employed for solving an optimization problem with

constraints and finding the optimum control variables of the building energy systems.

Model predictive control (MPC)

Model predictive control (MPC) is a control algorithm that derives the optimal control input for the target command and utilizes the moving horizon method (i.e., receding horizon method) in each timestep (Camacho and Bordons, 2007). The schematic of the MPC algorithm is described in Figure 1. The future control input within the discrete prediction horizon (H_p) at t timestep ($u_{t+p|t}$) is optimally obtained based on the objective function by the target command of the system. At this time, the matrix of $u_{t+p|t}$ can be determined based on the predicted control output within the prediction horizon at t timestep ($\hat{y}_{t+p|t}$), which can be obtained from the surrogate prediction model. Only the first control input matrix within the control horizon (H_c), $u_{t+c|t}$, is assigned as the actual control input, and the same process is repeated consecutively in the next calculation step to obtain a new control input.

Figure 1: Schematic of MPC algorithm.

Building and system configuration

In order to investigate the effect of MPC application, a case study was conducted utilizing simulation analysis. In this simulation analysis, a virtual structure located in Tokyo was assumed as a target building. Regarding the modeling software, OpenStudio version 2.3.0 (Guglielmetti, Macumber, and Long, 2011) and EnergyPlus version 8.5.0 (US DOE, 2016) were utilized. The weather data used for the simulation were from the Tokyo weather file, created by referring to the expanded Automated Meteorological Data Acquisition System (AMeDAS) (Akasaka et al., 2000) design weather data.

Model of the building

The target building assumed in this study was an eight-story office building with a total floor area of 6,110.56 m². Figure 2 shows the reference floor plan and overview of the target building. In Figure 2(a), the left area is the core space and the right area is the office space of the building. Air-conditioning was conducted only for the office space and the air conditioning area, which encompassed eight floors, was modeled as a single lumped thermal zone. The window-to-wall ratio, which represents the ratio of the window area to the total building envelope area, was set as 80%. The design flow rate of the building infiltration

Figure 2: Target building.

Figure 3: Schematic of building energy system.

was set as 0.0167 m³/s. The material properties of the building envelop were set as follows: exterior wall, 0.95 W/(m²K); roof, 0.49 W/(m²K); floor, 0.71 W/(m²K); and window, 2.97 W/(m²K). Additionally, the baseline of internal heat load elements was set as follows: occupancy density, 0.92 person/m²; metabolic heat gain from a person, 120 W/person; lighting, 10 W/m²; and equipment, 15 W/m². Only the cooling operation of the HVAC system was considered in this study. The cooling operation period was set from June 15 to September 15, during the weekdays at occupied hours from 9:00 to 18:00 with a cooling setpoint temperature of 26 °C.

Model of the system

The plant loops of the HVAC system considered in this study are described in Figure 3. The system consisted of four main components: one air-cooled chiller (Chiller) and one stratified chilled water thermal energy storage (TES) for the primary side, as well as two fan coil units (FCU₁, FCU₂) for the secondary side. The TES tank was assumed to have 10-layer temperature stratifications and the fans attached in fan coil units were set to a constant flow fan. As shown in Figure 3, four water loops were connected by three fluid-to-fluid heat exchangers (HEX₁–HEX₃) and five variable-speed pumps (Pump₁–Pump₅). The control variables in this system were the mass flow rates of Pump₁–Pump₅. The chiller outlet temperature was fixed at 4 °C, and the design temperature difference of each plant loop was set to 5 °C.

The nominal capacity of FCU₁ and FCU₂ was set to 150 kW so that each individual fan coil unit could have a 30% safety margin to the original thermal load of 114.5 kW, which is half of the cooling peak load of 229 kW. The nominal capacity of the chiller was set to 390 kW so as to have a 30% margin for 300 kW, which is the sum of the nominal capacity of the two fan coil units. The volume of the TES tank was set to 170 m³ to cope with a daily cooling load of 762.8 kW, which is about 40% of the maximum daily cumulative cooling load of 1907 kW during the cooling season.

Prediction models: ANN

In order to define an effective MPC, reliable but computationally light prediction models are necessary. This is especially important when we need to find optimal solutions for multiple control variables with increased numbers of parameters. For this reason, we utilized an artificial neural network (ANN) as a surrogate model to reduce the computational load. A total of four ANN prediction models were constructed to predict the following parameters: room temperature, temperature of the top and bottom layers inside the TES tank, inlet and outlet temperatures of the chiller, and the electricity consumption of the chiller. Input parameters were selected considering the relationship between the target parameter based on a trial and error approach (Table 1).

As regards the ANN structure, a 4-layer feedforward type composed of two hidden layers with 20 neurons was selected. The ANNs were trained using the simulation results obtained from EnergyPlus. To construct proper training data, 64 datasets were obtained by combining datasets as follows: random occupancy density, four sets; constant occupancy density with 25% intervals, 4 sets; random mass flow rate of pumps, four sets; and constant mass flow rate of pumps with 25% intervals, four sets. The total hourly data of 142,848 data ($= 93 \text{ d} \times 24 \text{ h} \times 64$ datasets) was obtained. In the training process, 70% of the data was classified for training, 15% for verification to prevent over-fitting, and the remaining 15% for evaluation purposes.

A coefficient of determination (R^2) and mean square error (MSE) were utilized to estimate the trained ANNs using a separated evaluation dataset. The R^2 of all ANNs was over 0.9 with a high accuracy (Table 1). Additionally, the MSEs were less than $0.07 \text{ }^\circ\text{C}$ for the predicted room

Table 1: Input and target data of ANNs and its evaluation result.

	Input data	Target data	R^2	MSE
1	$T_{out}^{t+1}, S_{diff}^{t+1}, S_{dir}^{t+1}, N_{occu}^t, T_{zone}^t, \dot{m}_{p1}^{t+1}, \dot{m}_{p2}^{t+1}, \dot{m}_{p3}^{t+1}, \dot{m}_{p4}^{t+1}, \dot{m}_{p5}^{t+1}$	T_{zone}^{t+1}	0.987	$0.051 \text{ }^\circ\text{C}$
2	$T_{TES,top}^t, T_{TES,bot}^t, T_{zone}^{t+1}, \dot{m}_{p1}^{t+1}, \dot{m}_{p2}^{t+1}, \dot{m}_{p3}^{t+1}, \dot{m}_{p4}^{t+1}, \dot{m}_{p5}^{t+1}$	$T_{TES,top}^{t+1}, T_{TES,bot}^{t+1}$	0.994	$0.039 \text{ }^\circ\text{C}$
3	$T_{out}^{t+1}, RH^{t+1}, T_{zone}^{t+1}, T_{c,in}^t, T_{c,out}^t, T_{TES,top}^{t+1}, T_{TES,bot}^{t+1}, \dot{m}_{p1}^{t+1}, \dot{m}_{p2}^{t+1}, \dot{m}_{p3}^{t+1}, \dot{m}_{p4}^{t+1}, \dot{m}_{p5}^{t+1}$	$T_{c,in}^{t+1}, T_{c,out}^{t+1}$	0.988	$0.074 \text{ }^\circ\text{C}$
4	$T_{out}^{t+1}, RH^{t+1}, T_{zone}^{t+1}, T_{TES,top}^{t+1}, T_{TES,bot}^{t+1}, T_{c,in}^{t+1}, T_{c,out}^{t+1}, \dot{m}_{p1}^{t+1}, \dot{m}_{p2}^{t+1}, \dot{m}_{p3}^{t+1}, \dot{m}_{p4}^{t+1}, \dot{m}_{p5}^{t+1}$	$C_{chiller}^{t+1}$	0.999	9.4 Wh

T_{zone} : Room temperature ($^\circ\text{C}$), T_{out} : Outdoor temperature ($^\circ\text{C}$), S_{diff} : Diffuse solar irradiation (W/m^2), S_{dir} : Direct solar irradiation (W/m^2), N_{occu} : Number of occupants (person), $\dot{m}_{pn}$: Mass flow rate of Pump_n (kg/s), $T_{TES,top}$: Temperature of top layer inside TES tank ($^\circ\text{C}$), $T_{TES,bot}$: Temperature of bottom layer inside TES tank ($^\circ\text{C}$), RH : Outdoor relative humidity (%), $T_{c,in}$: Inlet temperature of chiller ($^\circ\text{C}$), $T_{c,out}$: Outlet temperature of chiller ($^\circ\text{C}$), $C_{chiller}$: Electricity consumption of chiller (kWh), superscript t : present (t) timestep, superscript $t+1$: next ($t+1$) timestep

(a) Correlation analysis (b) Error histogram

Figure 4: Evaluation result of ANN to predict room temperature.

(a) Correlation analysis (b) Error histogram

Figure 5: Evaluation result of ANN to predict temperature of top and bottom layers inside TES tank.

(a) Correlation analysis (b) Error histogram

Figure 6: Evaluation result of ANN to predict inlet and outlet temperature of chiller.

(a) Correlation analysis (b) Error histogram

Figure 7: Evaluation result of ANN to predict electricity consumption of chiller.

temperature, temperature of the top and bottom layers inside the TES tank, and chiller inlet and outlet temperature. In regard to the predicted chiller electricity consumption, the MSE was 9.4 Wh. The correlation analysis and error histogram between target and predicted data in estimating trained ANNs are shown in Figure 4–Figure 7.

MPC implementation

It is necessary to clarify the prediction horizon and the control horizon prior to implementing the MPC algorithm. In this study, the prediction horizon was set to 24 h and

the control horizon was set at 1-h intervals. The control variables are the mass flow rate of five supply pumps in the plant system. Therefore, the MPC algorithm predicts the future states of the building and its energy system based on the ANN prediction results of up to 24 h and assigns the optimal control variables at 1-h intervals. The simulation was conducted for four days, from July 17 to July 20. For MPC implementation, a flow rate control was conducted via third-party software, BCVTB version 1.6.0 (Wetter, 2011).

Disturbances

In this study, an unexpected increase in occupants and the time-variant electricity pricing were considered as disturbances that could affect the MPC implementation for building energy management. In Figure 8, the two different occupant profiles are described. The baseline schedule refers to the basic occupant schedule of the target building, while the variation schedule refers to the sudden increase in the occupant heat loads. We intentionally assigned a significant disturbance with an altered occupant schedule to examine the robustness and effectiveness of the developed MPC algorithm. Further, the time-varying electricity pricing was considered as shown in Figure 9.

Objective function and constraints

The objective function and constraints for solving an optimization problem can be expressed as in Equations (1)–(6). The objective function (J_s) can be expressed as a function of the mass flow rate of five pumps ($\dot{m}_{\text{pump}}$) as shown in Equation (2), because they are the control variables of this plant system. In conclusion, the control objective is to minimize the operating cost by multiplying the sum of the electric consumption of the chiller (C_{chiller}) and five pumps (C_{pump}) by the hourly varying electricity price (P^t) within the prediction horizon (t_{H_p}) of 24 h.

The constraints are to maintain a room temperature of 26 °C and determine the pump flow rates under their maximum design flow rates. The electricity consumption of the pumps was predicted with the linear regression equation between the mass flow rate, as shown in Equation (6).

$$\text{Minimize}(J_s) = \sum_{t_{H_p}=1}^{24} \{ (C_{\text{chiller}}^t + C_{\text{pump}}^t) \times P^t \} \quad (1)$$

$$J_s = f(\dot{m}_{\text{pump}1}, \dot{m}_{\text{pump}2}, \dot{m}_{\text{pump}3}, \dot{m}_{\text{pump}4}, \dot{m}_{\text{pump}5}) \quad (2)$$

Subject to

$$T_{\text{zone}} \leq 26 \text{ } ^\circ\text{C}, \text{ at } 09:00\text{--}18:00 \quad (3)$$

$$\dot{m}_{\text{pump}1}, \dot{m}_{\text{pump}2} \leq 10.86 \text{ kg/s} \quad (4)$$

$$\dot{m}_{\text{pump}3}, \dot{m}_{\text{pump}4}, \dot{m}_{\text{pump}5} \leq 8.22 \text{ kg/s} \quad (5)$$

where

$$C_{\text{pump}}^t (\text{kWh}) = 0.2555 \times \dot{m}_{\text{pump}}^t \quad (6)$$

Figure 8: Condition of occupant disturbance.

Figure 9: Condition of time-variant electricity pricing.

Epsilon constrained differential evolution with random jumping (ϵ DE-RJ)

As an optimization method, we applied the metaheuristic epsilon constrained differential evolution with random jumping (ϵ DE-RJ) method. The ϵ DE-RJ algorithm can efficiently search for an optimized solution and solve the given problems with the objective function and constraints concurrently. Furthermore, it avoids being stuck at a local minimum by random jumping when the solution of a certain population in the following generations are the same. Further details on the ϵ DE-RJ algorithm and its effectiveness can be found in the paper by Ikeda, Choi, and Ooka (2017).

Based on the ϵ DE-RJ optimization algorithm, the number of population was set to 40 and the number of generations was set to 1,000. Therefore, a total of 4,000 iterative calculations were conducted per control timestep (1-h). Following completion of 4,000 numerical optimization calculations, the optimum mass flow rate of the five pumps was assigned as an actual control input and this process was updated consecutively.

Case study

To examine the effect of the developed MPC scheme in the presence of occupant and electricity pricing disturbances, a total of four cases were compared. In each case study, the MPC simulation results were compared with the rule-based control (RBC) results.

The RBC is one of the conventional control methods that has been widely adopted in building energy systems due to its simplicity when determining the control inputs. The RBC manages the control subject according to user-defined conditions or schedules. In this study, the RBC was defined as a TES priority operation. The TES was charged during unoccupied hours with a constant mass flow rate of 10.86 kg/s via HEX₁ and discharged during occupied hours with a constant mass flow rate of 8.22 kg/s.

via HEX₃. When the charged heat amount of the TES tank was insufficient to cope with the cooling load of the thermal zone, the chiller started parallel operation with the TES system.

A summary of the conditions of the four cases is given in Table 2. Case 1, in which the RBC was applied without considering any occupant or electricity pricing disturbances, was assumed as a baseline for the comparison. In Case 2, the RBC was applied considering the occupant disturbances but pumps were operated based on the same mass flow rates obtained in Case 1. Case 2 was formulated in order to examine the effect of the occupant increase on the room temperature. In Case 3, the occupant disturbance was applied, but the plant system was controlled by the RBC scheme without considering the varying electricity prices. In Case 4, the developed MPC was applied for optimum control considering both occupant and electricity pricing disturbances.

Table 2: Summary of case study conditions.

Case	Disturbance		Control strategy	Description
	Occupant	Electricity pricing		
Case 1	×	×	RBC	RBC with no disturbances
Case 2	○	×	RBC	RBC with occupant disturbance but controlled by pump mass flow rates from Case 1
Case 3	○	×	RBC	RBC with occupant disturbance
Case 4	○	○	MPC	MPC with occupant and electricity pricing disturbances

Results

Room temperature

Figure 10 shows the simulation result of the room temperature for each of the four cases. In comparison with Case 1 which is the baseline for comparison, in Case 2, where the occupant increase occurred and the mass flow rates of five supply pumps from Case 1 were applied for the plant operation, the room temperature exceeded the setpoint of 26 °C during occupied hours. This is because the supplied flow rates were insufficient to remove the increased cooling loads corresponding to the occupant disturbance. Therefore, we found that it is important to take into account unexpected occupant disturbances in the operational phase. In all cases, except for Case 2, the room temperature was well maintained at the HVAC cooling setpoint temperature of 26 °C during occupied hours, i.e., from 09:00 to 18:00.

Pump operation

Figure 11 shows the control result of the mass flow rate of five different supply pumps in Case 3 and Case 4. Because the RBC takes a TES priority operation strategy based on the charging and discharging schedule, all

pumps except for Pump₅ were controlled at a constant mass flow rate in Case 3. In Case 3, Pump₅ was operated at a minimum because the chiller operates only when the charged heat amount of TES cannot deal with the thermal loads. However, the MPC strategy estimated the system behavior within the next 24 h, in every 1 h intervals, and identified the optimum mass flow rate to minimize operation costs. Therefore, all of the five supply pumps were optimally manipulated in Case 4.

Figure 10: Controlled result of room temperature in each case.

Figure 11: Controlled result of pump mass flow rate in Case 3 (RBC) and Case 4 (MPC).

Electricity consumption

Figure 12 and Figure 13 show the result of the electric consumption of the chiller and pump in Case 3 and Case 4. As the figures show, the chiller accounts for a significant portion of the total energy use for the building energy systems. Therefore, if the chiller operation can be optimally controlled considering hourly electricity price variations, then it is the most appropriate solution for reducing the total operating costs.

In this respect, Case 4 has succeeded in correctly determining the chiller operation rate by optimally manipulating the mass flow rate of its supply pump (Figure 12 and Figure 13). In Case 4, at certain moments, the electric consumption exceeded that of Case 3, but this can be interpreted as the MPC strategy recognizing that operating a chiller instantly can reduce the cumulative operating cost within the next 24 h.

Figure 12: Result of energy use in Case 3 (RBC).

Figure 13: Result of energy use in Case 4 (MPC).

Figure 14: Result of total operation cost in each case.

Operation cost

Figure 14 shows the result of operating costs in each case. By implementing the MPC strategy, Case 4 reduced the operation cost by 4.1–20.5% compared to the RBC strategy of Case 3. In conclusion, Case 4 saved the total operating cost for the four-day simulation period by 8.3%.

Conclusion

This paper investigated the application effect of a model predictive control (MPC) strategy for building energy systems with thermal energy storage (TES) using an artificial neural network (ANN) to predict the behavior of building energy systems within 24 h. Further, epsilon constrained differential evolution with random jumping (ϵ DE-RJ) was implemented as an optimization algorithm for seeking optimal control variables with constraints to minimize the operation cost. We intentionally assigned a significant occupant disturbance to confirm the ability of MPC to cope with future disturbances.

The simulation results of the MPC strategy were compared with the conventional rule-based control (RBC) strategy. In conclusion, it was observed that MPC reduced the operation cost by approximately 8.3% during the four-day simulation period compared with the RBC strategy. In the future, we intend to conduct a validity study of the MPC scheme with an experimental analysis and verification process to assess wider applicability considering various conditions of possible operational disturbances in building energy systems.

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