Master’s Thesis of Engineering

Stochastic Approach for Model-Predictive Control of a Variable Refrigerant Flow System

VRF 시스템 최적제어의 확률적 접근

August 2023

Department of Architecture and Architectural Engineering

College of Engineering

Seoul National University

Seo-Hee Choi

Stochastic Approach for Model-Predictive Control of a Variable Refrigerant Flow System

Advised by Prof. Cheol-Soo Park

Submitting a Master’s Thesis of Engineering

August 2023

Department of Architecture and Architectural Engineering

College of Engineering

Seoul National University

Seo-Hee Choi

Confirming the master's thesis written by

Seo-Hee Choi

August 2023

Chair	Myoung-Souk Yeo	(Seal)
Vice Chair	Cheol-Soo Park	(Seal)
Examiner	Sun Sook Kim	(Seal)

Abstract

It has been widely acknowledged that technical building performance can be influenced by many uncertain factors such as weather, scenarios, occupant behavior, simulation parameters, and numerical methods. For objective and reproducible performance assessment, the aforementioned uncertainties must be reflected in the performance simulation analysis.

With this in mind, the authors present a stochastic assessment of model predictive control (MPC) performance of a variable refrigerant flow (VRF) cooling system for an office space. The office space was modeled using EnergyPlus, and surrogated models were employed for MPC studies. It is found that the energy savings by MPC can be highly stochastic, ranging from 0.2% to 26.8% depending on weather data. Moreover, the uncertainty in MPC performance was significant, as evidenced by the notable differences in energy saving distributions observed between five different building usage scenarios.

Furthermore, this study focuses on analyzing operational MPC strategies for a VRF system. The results show that the MPC adapts its control strategies based on different load conditions. The "drifting strategy" is optimal for low cooling load days, while the "high COP strategy" is more energy-efficient for high cooling load days. The advantage of each strategy changes at the inflection point (PLR = 33%), which is influenced by the dynamic characteristics of the system's COP and the thermal behavior of the room.

Keyword : model predictive control, uncertainty, artificial neural network, variable refrigerant flow system, objective performance assessment, control strategies, COP

Student Number : 2021-29883

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

1.1. Background

Buildings account for approximately 40% of global energy consumption, with the operational phase being the primary contributor. Consequently, it is crucial to reduce energy consumption and operating costs during this phase of the building's life cycle. Moreover, the control of heating, ventilation, and air conditioning (HVAC) systems is complex due to intricate interplay among various subsystems such as chillers, boilers, heat pumps, pipes, ducts, fans, pumps, heat exchangers, blinds, and lightings. The inherent complexity arises from a combination of these nonlinear dynamics in buildings and the presence of time-varying disturbances. As a result, there has been a growing demand for the development and implementation of efficient HVAC control technologies and strategies.

Model predictive control (MPC) has been widely used in the building industry due to its energy saving potential. MPC employs optimization techniques to determine the optimal control variables that minimize a predefined cost function over a specific prediction time horizon (Afram and Janabi-Sharifi, 2014). Numerous studies have proven that energy efficiency can be enhanced by advanced HVAC control with average energy savings of 13% to 28% (Gyalistras et al., 2010; del Mar, Alvarez, de A., and Berenguel, 2014; Roth et al., 2002). Liang et al. (2015) implemented MPC of an air handler for multi-zone VAVs for 9 days (01 Jul.-09 Jul.) and achieved energy savings of 25.7%. Ma et al. (2012) saved the energy consumption of a VAV system by 24.31% for 7 days in July. As reported in many MPC studies (IBPSA 2001-2021), the MPC performance has been assessed with fixed simulation parameters for a certain period of time in *a deterministic fashion.* The short-term experiments last only weeks to months, limiting the insight on how MPC strategies perform during all seasons (Drgona et al., 2020).

Since de Wit (2001), MacDonald (2002), and Hopfe (2009) studies, it has been widely acknowledged that a whole building performance assessment or any technical system performance assessment (e.g. chiller, AHU, cooling tower, etc.) can be biased by epistemic and aleatory uncertainties. Tian et al. (2018) reported different types of uncertainties in buildings including weather, thermal properties of building envelopes, occupant behavior, HVAC system's specification data, and simulation parameters (e.g. heat transfer coefficients). Without taking the impact of such uncertainties in assessing the technical system performance, significant performance gap can occur (de Wilde, 2014).

Several MPC studies have been reported to deal with the aforementioned uncertainties. Ma, Matusko, and Borrelli (2015) used stochastic weather information to develop a stochastic model-predictive control of building HVAC systems. Li, and Wang (2022) cross-compared several MPC strategies under uncertainties for optimal utilization of resources in buildings.

In this paper, the authors present that MPC performance of a variable refrigerant flow (VRF) cooling system for the entire cooling season (01 May – 30 Sep.) can be highly stochastic and thus, its performance must be assessed in *a stochastic fashion.* For this study, a typical office space equipped with the VRF cooling system was selected. Based on simulation results from EnergyPlus, two surrogated models were developed to predict energy consumption of the VRF and indoor air temperature. It is addressed in the following sections that there is significant variation in energy savings by MPC depending on uncertain and unknown variables. In addition, it is discussed how MPC itself finds optimal control strategies under different conditions.

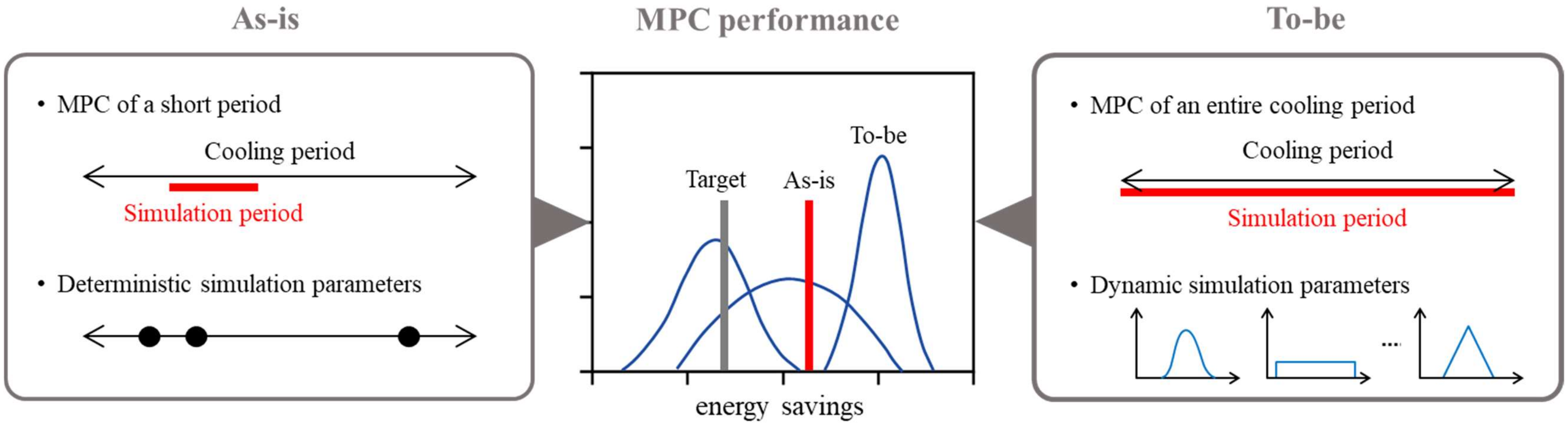


Figure 1 As-is and To-be states of MPC performance assessment

1.2. Research Process

In this thesis, the author investigates the stochastic nature of MPC performance and highlights the need for a probabilistic approach in assessing MPC performance, along with detailed analysis of daily energy savings.

- **Step 1**: Construct a building energy model

  This step involves developing a detailed building energy model using EnergyPlus that represents the thermal characteristics, room dynamics, HVAC systems, and energy consumption patterns of the target building.

- **Step 2**: Select parameters for uncertainty analysis

  The author selects parameters that contribute to uncertainties in MPC performance. Five building usage scenarios are identified in order to understand the variability and impact of uncertainties on MPC performance.

- **Step 3**: Build a surrogate model

  To facilitate efficiency, the author constructs a surrogate model using Artificial Neural Networks (ANN). The surrogate model serves as a simplified representation of the complex building energy model and can rapidly predict the building's response to different control inputs. The models are trained using data from the original building energy model of EnergyPlus, which is generated using Latin hypercube sampling on the input variables.

- **Step 4**: Set up MPC algorithm and conduct MPC for a whole cooling period

  In this step, the author develops an MPC algorithm tailored to the specific cooling requirements of the building, considering the uncertainty parameters identified in Step 2. The MPC algorithm optimizes control actions over a whole cooling period, aiming to minimize energy consumption while meeting comfort requirements.

- **Step 5**: Conduct uncertainty analysis of MPC performance

  In this step, an uncertainty analysis is conducted to assess the performance of the MPC under different building usage scenarios mentioned in step 2. The energy savings are compared as distributions of the whole cooling period.

- **Step 6**: Conduct energy saving analysis of MPC based on different conditions

  Energy-saving analysis is carried out to demonstrate the effectiveness of MPC strategies under different conditions. Daily controls between different weather conditions and occupancy schedules are compared. The control strategies are comprehended by considering the COP dynamics of the system.

1.3. Thesis Outline

The objectives and the necessity of this study have been discussed. The contents of the following chapters are as follows:

- Chapter 2 presents general backgrounds and schemes of model predictive control (MPC) in order to provide clearer understanding of this thesis.
- Chapter 3 describes the properties and settings of the simulation model: the target building; building usage scenarios for uncertainty analysis of MPC performance; and the surrogate models which are the predictors used for predicting future states.
- Chapter 4 illustrates the results and findings after performing MPC for a whole cooling season with five different building usage scenarios. The comparison between MPC results show its uncertainties, and proposes a stochastic approach. Moreover, daily MPC control analysis is illustrated in detail for a thorough understanding of MPC.
- Chapter 5 closes the thesis by demonstrating the conclusion and discussing the limitations and future works of the study.

Chapter 2. Literature Review

MPC is an optimal control strategy that generates the optimal control inputs by minimizing a certain cost function over a finite prediction horizon, with disturbances and constraints. The mathematical model of the building and its systems, the current state measurements, and weather forecast are used to predict and optimize the future behavior of the building (Drgona, 2020). Figure 2 illustrates a typical MPC scheme with x_k, y_k, u_k, N each denoting state values, outputs, control action inputs, and prediction horizon.

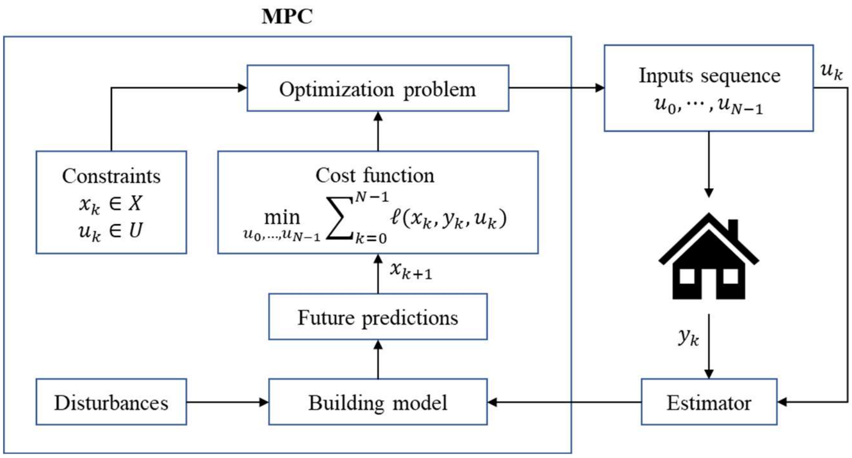


Figure 2 Schematic representation standard MPC
(revised from Drgona et al., 2020)

A typical MPC system consists of a system model, a cost function, constraints, a disturbance model, an optimization method, and a control horizon, with all of them impacting MPC performance.

- The model of the building and its system must be able to describe nonlinear and discontinuous phenomena, and processes occurred in buildings. The accuracy of the model influences the quality of MPC, while the simplicity of the model is also important for low computational demand and MPC implementation. Physics-based models, based on the principles of heat transfer and conservation of energy and mass, are accurate and reliable, but require significant effort. Data-driven black-box models have lower development cost, but require more training data (Afroz et al., 2018), and lack reliability when they are deployed outside the training range (Afram & Janabi-Sharifi, 2014). Gray-box models are modeled with simplified physical data with parameter estimation based on measured data, making them reliable, adaptable, transferable, and in need of fewer data (Boodi et al., 2018).

- The cost function, also called the objective function, is the performance target based on the desired behavior of the building that needs to be minimized. It can be configured as a tracking error, control effort, energy cost, demand cost, power consumption, or a combination of these factors (Cigler et al, 2013; Cupeiro Figueroa, Cigler, and Helsen (2018).

- The MPC can find solutions that does not violate the given constraints of the inputs, outputs and actuators. The constraints are used commonly for limiting selected variables within given ranges, e.g., heat fluxes and room temperatures (Picard et al., 2017), supply air temperatures (Rehrl

& Horn, 2011) and airflow rates (Huang, 2011).

- The internal and external disturbances refer to non-controllable inputs that act on the systems. They must be considered for the accurate prediction of the future state. Some examples are weather, occupant activities, equipment use, internal heat gain and solar irradiation.

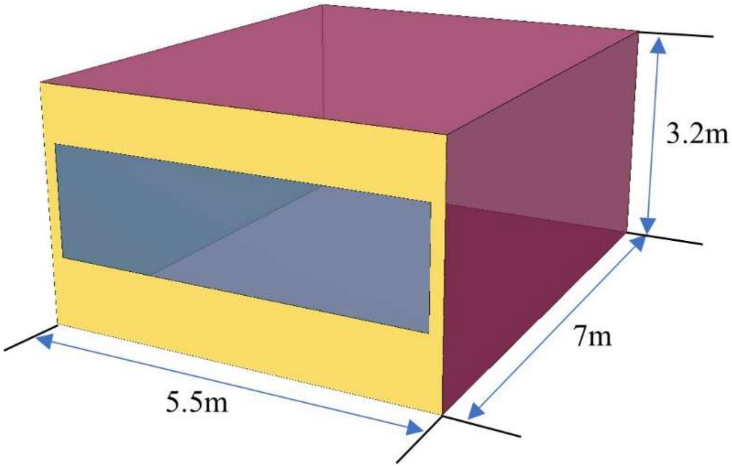
MPC inevitably face challenges due to the mismatch between the actual plant behavior and the model used for control, and inaccurate or corrupted measurements. There are two main types of uncertainties: parametric uncertainties and non-parametric uncertainties. Parametric uncertainties stem from errors in the models caused by unknown parameters, inaccurate equations, or components that do not function as intended. On the other hand, non-parametric uncertainties are generated by uncertainties in measurements and predictions of factors like ambient temperature, solar irradiation, inaccuracies in temperature sensors, limited sensor availability, and unmeasured disturbances such as window openings (Drgona, 2020). Many studies have searched for methods to mitigate the effects of these uncertainties on MPC performance, e.g., offset-free MPC, robust MPC, stochastic MPC, adaptive MPC, and learning-based MPC, but despite these attempts, uncertainty is indispensable (Hopfe, 2009; MacDonald, 2002; Muske and Badgwell, 2002, Tian et al. 2018): they should be taken into consideration when assessing its performance.

Comparison and assessment of MPC are crucial in determining the most effective approach and implementing in real buildings. However, there are several challenges that make this process difficult. The variation in methods, factors and components of MPC result in a very large solution space, with each application having their own characteristics. Compared to this large available solution space, only a small number of field tests are available for short-term studies which is not enough to gain desirable insight. The metrics used in assessments are also diverse including energy savings, operating costs savings, occupant comfort improvement, computer hardware and software requirements, computation time, robustness to changing conditions, data requirements, implementation effort, and installer expertise. The lack of an official performance indicator makes the objective comparison more difficult.

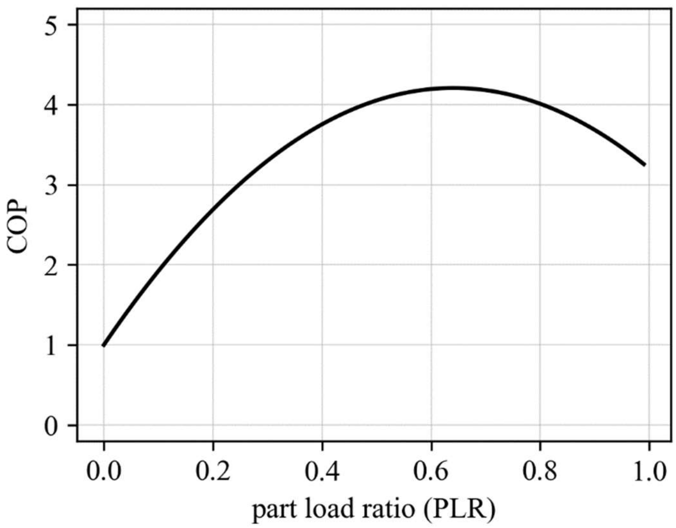
Chapter 3. Simulation Model

3.1. Target Building

The target building is a single-story office located in Gyeong-gi, South Korea (Figure 3 (a)). It consists of a single zone with a floor area of 38.5m2 (7m × 5.5m). The space has a south-facing window with a window-wall-ratio of 50%. Table 1 shows the details of the target space, with the thermal properties of the envelopes selected according to Korean building energy standards (KBES) (2022). The boundary conditions for all surfaces except the south-facing surface were set as adiabatic because this office was surrounded by identically conditioned spaces. The target building was modeled using EnergyPlus developed by the US DOE. It is assumed that the VRF system provides cold air during the cooling season. The VRF system changes the refrigerant mass flow rate with a variable speed compressor to meet the given cooling load (Aynur 2010). The total capacity of the VRF system is 6,000W with a rated coefficient of performance (COP) of 3.2. The COP curve of the VRF system was simplified as shown in Equation 1, which was provided by the VRF manufacturer. Please note that in Equation 1, the highest COP is 4.2 at 60% of the part load ratio (PLR) (Figure 3 (b)).



(a) Target space



(b) COP curve of VRF system

Figure 3 Target building

$$COP = -7.8 \times PLR^2 + 10 \times PLR + 1 \tag{1}$$

Table 1 Target office parameters according to Korean building energy standards (2022)

<table>
<tr><th colspan="2">Parameters</th><th colspan="2">Values</th></tr>
<tr><td rowspan="8">Office</td><td>Location</td><td colspan="2">Gyeong-gi, South Korea</td></tr>
<tr><td>Total floor area [m^2]</td><td colspan="2">38.5</td></tr>
<tr><td>Number of floors</td><td colspan="2">1</td></tr>
<tr><td>Ceiling height [mm]</td><td colspan="2">3200</td></tr>
<tr><td>WWR [%]</td><td colspan="2">50</td></tr>
<tr><td rowspan="2">U-value [W/m^2·K]</td><td>Wall</td><td>0.15</td></tr>
<tr><td>Window</td><td>0.9</td></tr>
<tr><td>Fenestration SHGC</td><td colspan="2">0.4</td></tr>
<tr><td rowspan="2">Cooling system</td><td>Cooling capacity [W]</td><td colspan="2">6,000</td></tr>
<tr><td>Rated COP</td><td colspan="2">3.2</td></tr>
<tr><td rowspan="3">Scenario</td><td>Occupant density [m^2/person]</td><td colspan="2">9.0</td></tr>
<tr><td>Equipment density [W/m^2]</td><td colspan="2">11.5</td></tr>
<tr><td>Lighting density [W/m^2]</td><td colspan="2">8.0</td></tr>
</table>

3.2. Building Usage Scenarios

In order to investigate the impacts of different factors to the uncertainty of energy savings by MPC, five different building usage scenarios were identified. As mentioned in Table 2, each scenario consists of different combinations of desired indoor temperature ($T_{desired}$), and occupancy schedule (Occ). Scenario I, II, III varies in the occupancy schedule with the desired room temperature of 24°C, while Scenario I, IV, V vary in the desired room temperature with the occupancy schedule of Occ 1.

Figure 4 presents the different occupancy schedules of OCC 1, OCC 2, and OCC 3. In OCC 1, the occupant density is constant during its operating hours (8:00 – 18:00) with a value of 1.0. Meanwhile, the occupant density of OCC 2 and OCC 3 is assumed to vary stochastically from 0.0 to 0.7 during operational hours. OCC 2 operates for the longest hours until late evenings (7:00 – 22:00), and OCC 3 starts operating earlier (6:00 – 19:00) than other schedules, with high occupant density on mornings and early afternoons.

Table 2 Building usage scenarios

	Desired indoor temperature [℃] $T_{desired}$	Occupancy schedule Occ
Scenario I	24℃	Occ 1
Scenario II	24℃	Occ 2
Scenario III	24℃	Occ 3
Scenario IV	23℃	Occ 1
Scenario V	25℃	Occ 1

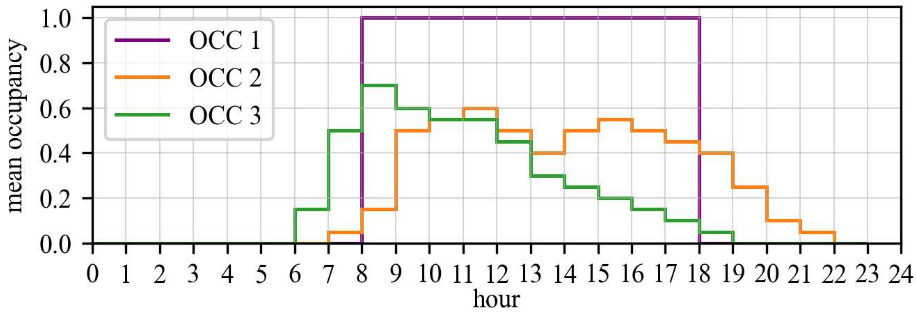


Figure 4 Occupancy schedules

3.3. Surrogate Model

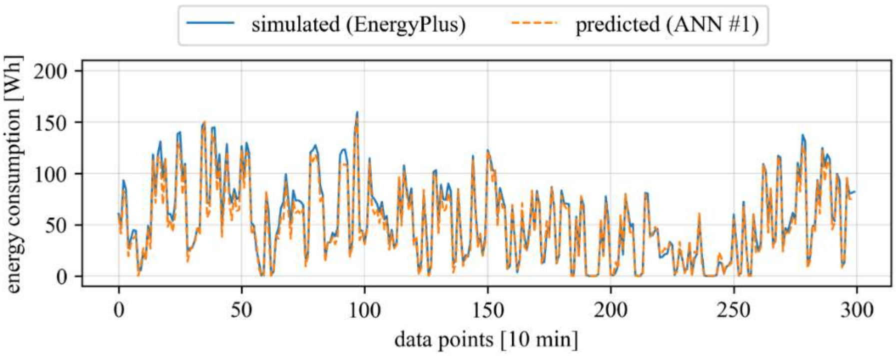
For the past decades, artificial neural network (ANN) has been successfully applied for estimating heating and cooling demands (Yokoyama, Wakui, and Satake 2009), predicting indoor environmental conditions (Moon, Yoon, and Kim 2013), and describing non-linear dynamics of cooling and heating systems (Ahn et al. 2020). Because an ANN model is capable of describing the dynamic characteristics of mechanical systems as well as the thermal behavior of buildings, an ANN model has been used as a surrogate model in many MPC studies (IBPSA 2001-2021).

In this study, two ANN models were developed in order to predict the future states for the prediction time horizon. As will be explained in Chapter 4, the MPC algorithm must exhaustively search for 729 control actions at each timestep, and the use of ANN models will make it more practical in that it lowers the computational costs without compromising the ability to mimic the dynamic behaviors of the building and its system. The two ANN models predict the energy consumption of the VRF system and supply fan (ANN #1) and indoor air temperature of the target space (Figure 1) (ANN #2), respectively. ANN #1 uses three state variables (indoor/outdoor air temperatures and solar radiation) and two control variables (set-point air temperature and supply air flow rate) as inputs, as shown in Table 2. ANN #2 uses the aforementioned three state variables, heat removal rate obtained from ANN #1, and two control variables (set-point air temperature and supply air flow rate) as inputs (Table 2). The input state variables are selected as the minimum information related to the VRF system that can be measured in actual buildings. The ANN parameters were determined using a trial-and-error method (hidden layers: 4, hidden nodes: 30, epochs: 1000, activation function: rectified linear unit (ReLU), optimization method: adaptive moment estimation (Adam), and loss function: mean squared error (MSE)).

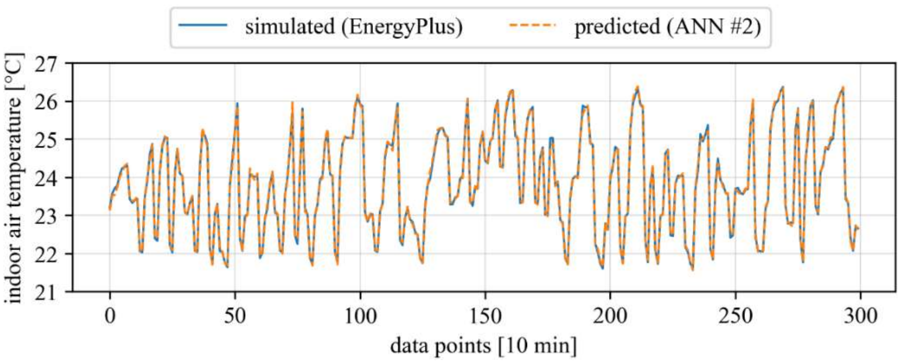
The control and prediction time horizons were set to 10 minutes and 30 minutes respectively so that the control actions can vary at the interval of 10 minutes based on the predicted state variables over the next 30 minutes. Train (80% of the total) and test (20% of the total) data were generated by EnergyPlus pre-simulation from 01 May to 30 Sep. Figure 5 compares the ANN model predictions of the test data to the actual values of EnergyPlus simulation. The ANN models showed reliable accuracy in predicting the dynamic behavior of the VRF system and the indoor environment with the coefficients of variance root mean square error (CVRMSE) within 9.7% and 0.3%.

Table 3 Inputs and outputs of ANN models

Model	**Variables**			**Timesteps**
ANN #1	Inputs	State variables	Indoor air temperature [°C, IAT]	t-2 t-1 t
			Outdoor air temperature [°C, OAT]	
			Global solar radiation incident on vertical surface [W/m^2, I_G]	
		Control variables	Set-point air temperature [°C, SET]	t+1 t+2 t+3
			Supply air flow rate [L/s, SA]	
	Outputs	Energy consumption by VRF and supply fan [Wh]		
		Heat removal rate [W]		
ANN #2	Inputs	State variables	Heat removal rate obtained from ANN #1 [W]	t-2 t-1 t
			Indoor air temperature [°C, IAT]	
			Outdoor air temperature [°C, OAT]	
			Global solar radiation incident on vertical surface [W/m^2, I_G]	
		Control variables	Set-point air temperature [°C, SET]	t+1 t+2 t+3
			Supply air flow rate [L/s, SA]	
	Outputs	Indoor air temperature [°C, IAT]		



(a) Energy consumption by ANN #1 (CVRMSE = 9.7%)



(b) Indoor air temperature by ANN #2 (CVRMSE = 0.3%)

Figure 5 Comparison between simulated (EnergyPlus) vs. predicted (ANN)

Chapter 4. MPC results

4.1. Virtual Experiment Conditions

The simulation was carried out using EnergyPlus, a dynamic simulation tool, for a cooling period in South Korea (01 May – 30 Sep). The control horizon is one timestep with a control action being maintained for 10 minutes (Figure 6). The prediction horizon is three timesteps and thus, three control actions take place for 30 minutes. As demonstrated in Figure 7, for every 3 timesteps, the predictor predicts the energy consumption of the VRF and the indoor air temperature for the next prediction horizon (30 minutes). The predictor uses the possible future control actions and the state variables of the past, which are the outputs of the previous simulation of EnergyPlus. The possible control actions consist of three options for the set-point air temperatures ($T_{desired}$-1℃, $T_{desired}$℃, $T_{desired}$+1℃) and three options for the supply air flow rates (low (150 L/s), mid (190 L/s), high (230 L/s)), resulting in 9(=3×3) control actions for each timestep (10 minutes) and a total of 729(=9^3) control actions for one prediction horizon (30 minutes). The optimizer exhaustively examines all 729 possible actions for the next prediction horizon. It selects the best control action that minimizes the cost function denoted by J, or energy consumption of the VRF's cooling energy over the prediction time horizon while maintaining the indoor air temperature in the range of [$T_{desired}$-1℃, $T_{desired}$+1℃]. Finally, the selected control action is fed back to the EnergyPlus, and the next three timesteps are simulated. This MPC process is repeated every three timesteps.

For comparison, a baseline VRF control was assumed as follows: the set-point air temperature is 24℃, and the supply air flow rate is 230 L/s. Depending on the room's instantaneous cooling load, the VRF automatically controls the current refrigerant's flow rate without depending on any predicted state variables. Thus, the only difference between the baseline control and MPC is whether the predicted state variables are employed or not in determining the control actions.

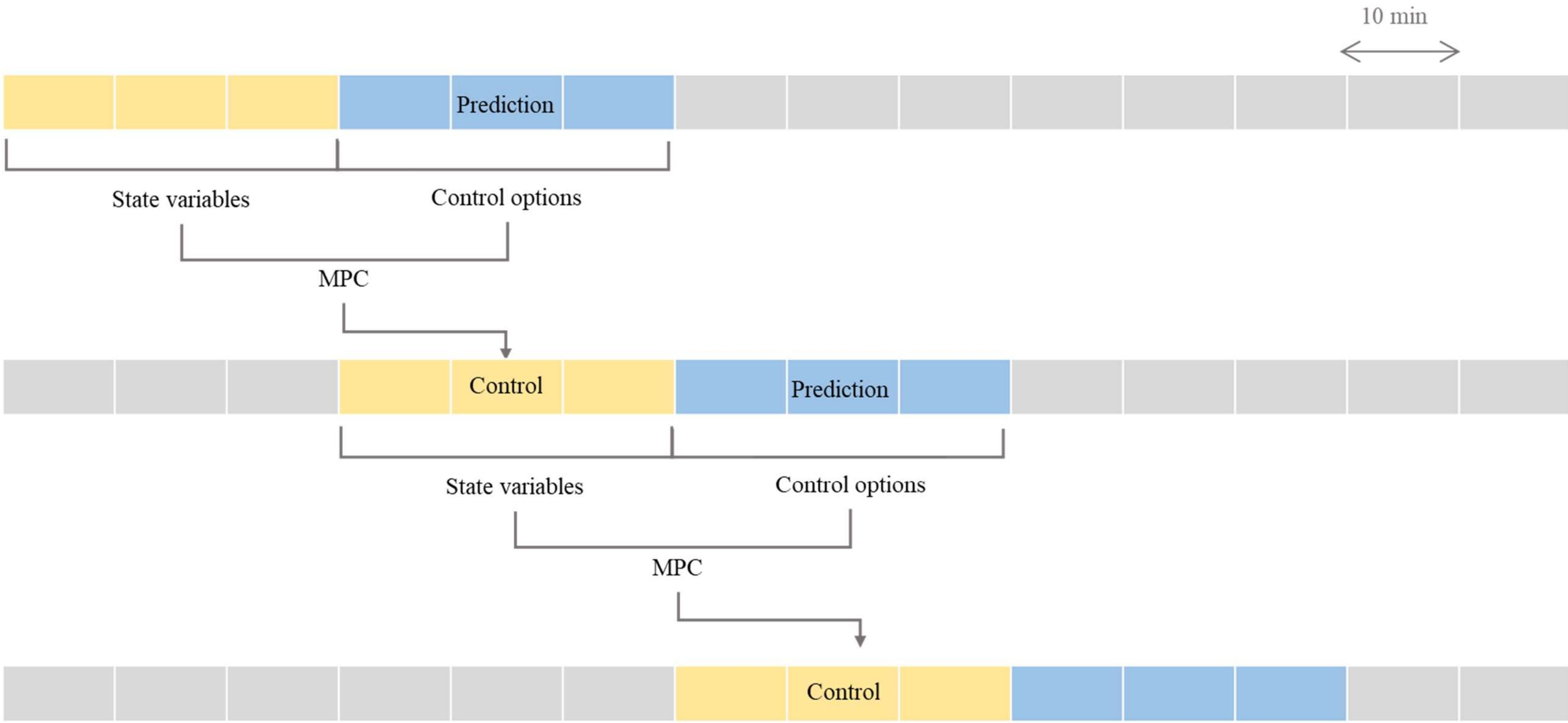


Figure 6 MPC timesteps

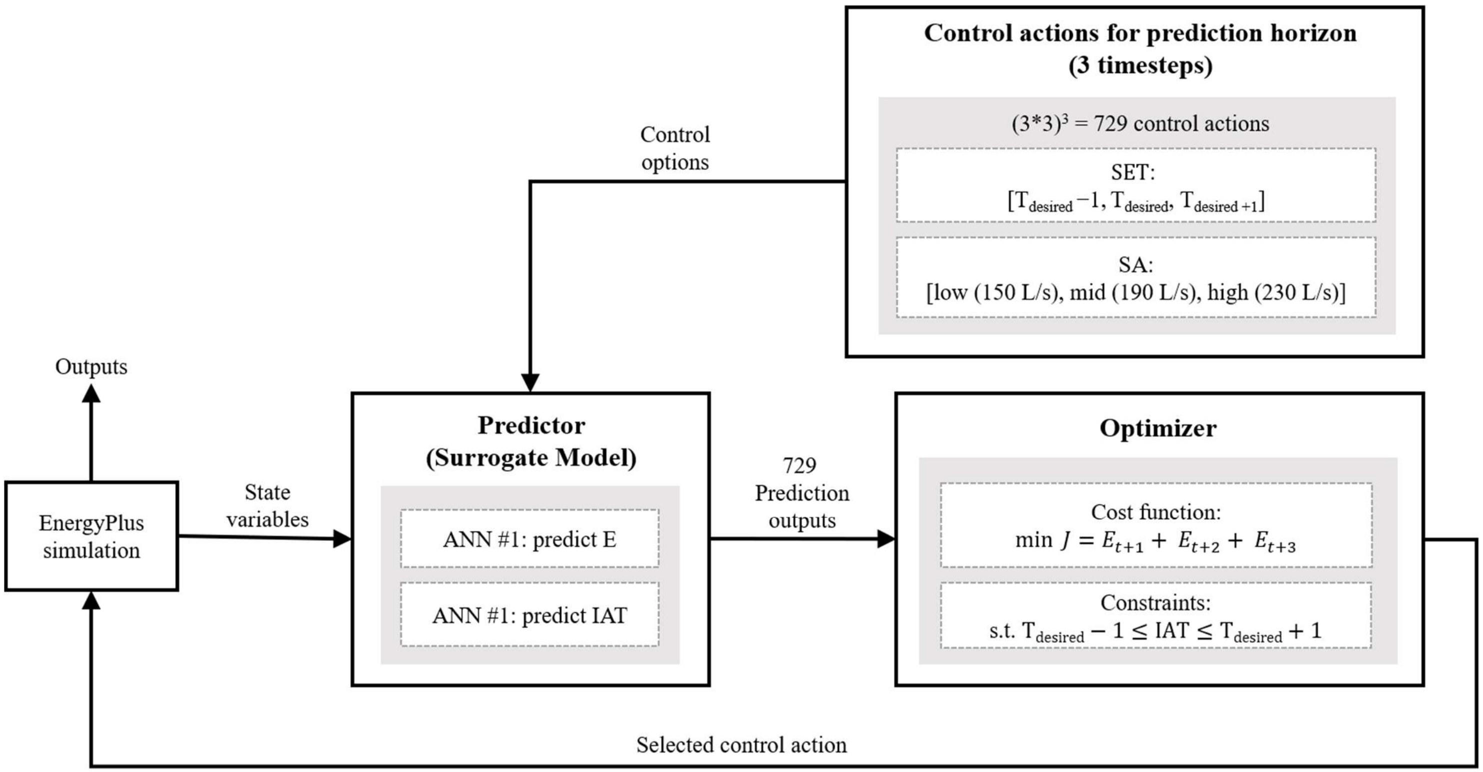


Figure 7 MPC process

4.2. Uncertainty Quantification in MPC Performance

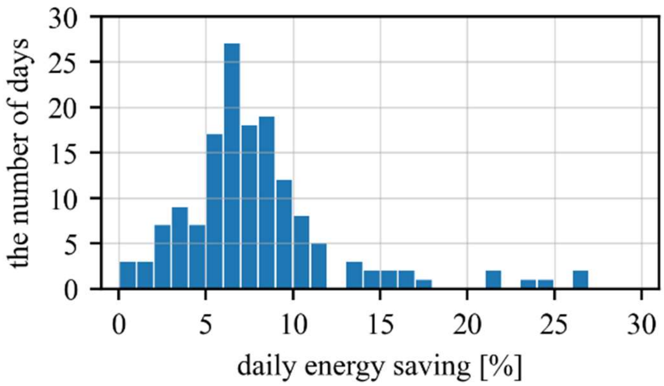
In order to investigate the uncertainty of energy savings by MPC and analyze the daily variations in MPC performance, the simulation was carried out for the whole cooling period in South Korea (01 May – 30 Sep) with five different building usage scenarios. Figure 8 shows the distributions of daily energy savings by MPC based on different scenarios. The uncertainty of MPC performance based on scenario variables is explained as follows:

- The energy savings of MPC exist stochastically depending on the weather conditions (Scenario I): The daily energy savings of Scenario I range from 0.2% (28 Jul) to 26.8% (10 May) with an average of 8.3%. The standard deviation (5.5%p) is non-negligible in that it equals 66.3% of the average value. It can be inferred from this result that the performance of MPC shows significant uncertainty depending on the outdoor environment (OAT, IG). In addition, it implies that the performance of a short period is not sufficient to represent the performance of the whole period.

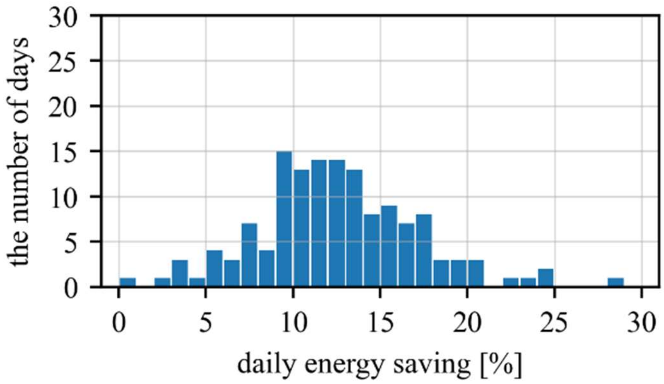
- The energy savings and the uncertainty of MPC performance can vary depending on the occupancy schedule (Scenario I vs. Scenario II vs. Scenario III): As mentioned earlier, the occupancy schedules differ in both the occupant density and the operating hours. The average daily energy savings exhibit a notable disparity across the scenarios, with a maximum difference of 6.1%p (8.3% vs. 12.6% vs. 14.4%). Also, the standard deviation of Scenario III is 1.6 times that of Scenario II (5.5%p vs. 4.6%p vs. 7.2%p). The distribution of daily energy savings in Scenario III yields both the highest average and standard deviation. This can be attributed to the reduced cooling load resulting from low occupant density and the high variance in occupant density over time. These observations highlight the significance of considering the inherent variability in occupancy patterns to accurately assess the effectiveness and uncertainties associated with MPC performance.

- The impact of occupant behavior ($T_{desired}$) on the uncertainty of energy savings is relatively small (Scenario I vs. Scenario IV vs. Scenario V): The maximum difference between the average daily energy savings is 3.4%p (8.3% vs. 7.3% vs. 10.0%), and the standard deviation also shows no significant difference (5.5% vs. 4.8% vs. 6.3%). Thus, when quantifying the uncertainty of MPC performance, it is necessary to reflect the interactions between the external environment (OAT, IG), the internal environment (occupancy schedule, internal heat gain), the systems that make up a building, and the building's whole self.

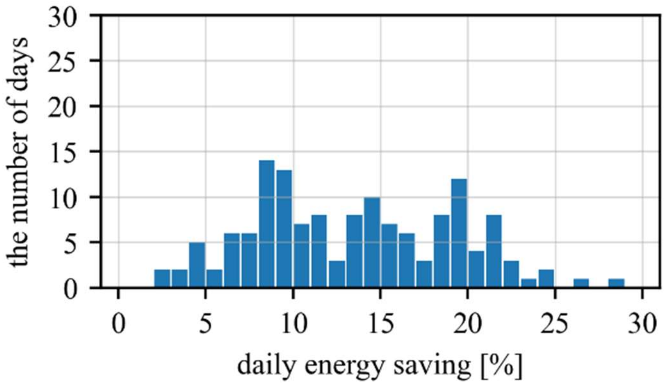
The analysis of daily energy savings by MPC shows that its stochastic nature must be carefully reflected when assessing MPC performance. In addition, it can be inferred that for the objective assessment of MPC performance, other uncertain variables must also be considered, e.g., indoor heat generation from lights, equipment, infiltration/ventilation, etc.



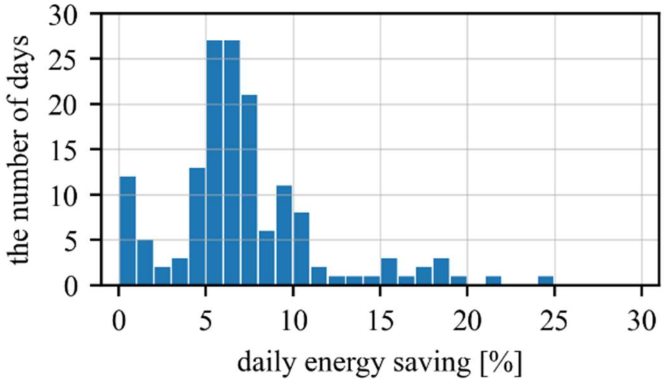
(a) Scenario I: $T_{desired}$ = 24°C, Occ 1 (8.3% savings)



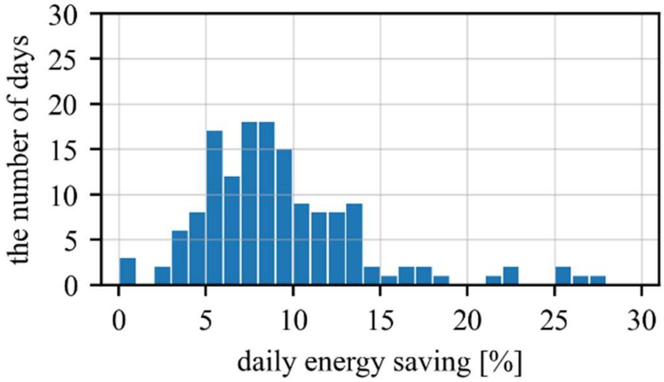
(b) Scenario II: $T_{desired}$ = 24°C, Occ 2 (12.6% savings)



(c) Scenario III: $T_{desired}$ = 24°C, Occ 3 (14.4% savings)



(d) Scenario IV: $T_{desired}$ = 23°C, Occ 1 (7.3% savings)



(e) Scenario V: $T_{desired}$ = 25°C, Occ 1 (10.0% savings)

Figure 8 Distribution of daily energy savings by MPC
(01 May – 30 Sep, 154 days)

4.3. Optimal Control Strategies of MPC

Figure 9 shows the relationship between the sum of hourly cooling loads and the daily energy savings by MPC of Scenario I. The daily energy savings by MPC tend to increase as the sum of hourly cooling loads approach the extremes. Table 4 shows environmental data, the sum of hourly cooling loads, and energy savings by MPC of three specific days; 11 May, 08 Jun, 07 Aug. These days were chosen to each represent low, medium, and high cooling load conditions. In Figure 9, the energy savings corresponding to these days are depicted by blue, yellow, and red dots. Interestingly, despite the nearly threefold difference in the sum of hourly cooling loads between 11 May and 07 Aug, they exhibit similar levels of energy savings. Conversely, the energy savings achieved on 08 Jun is considerably lower compared to the other days.

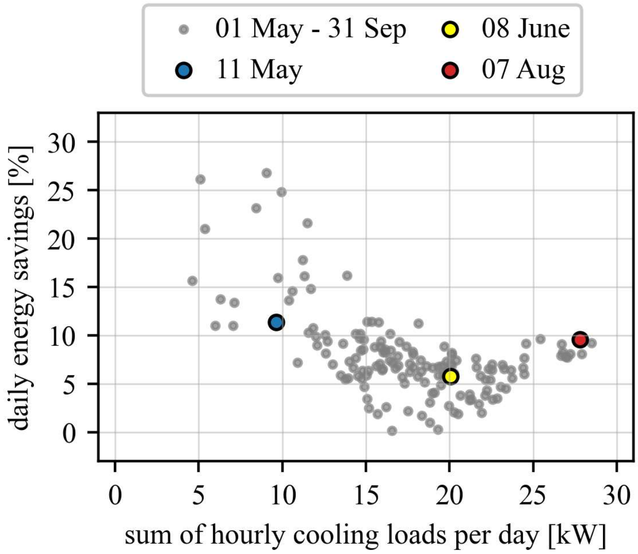


Figure 9 Daily energy savings by MPC in relation to the sum of hourly cooling loads per day

Table 4 Outdoor environmental conditions and energy savings by MPC

	Average OAT ('C)	Average I_G (W/m^2)	Sum of hourly cooling loads (kW)	Energy savings by MPC
11 May	17.4	139.1	9.6	11.4 %
08 Jun	25.7	120.9	20.0	5.7 %
07 Aug	31.5	124.9	27.8	9.5 %

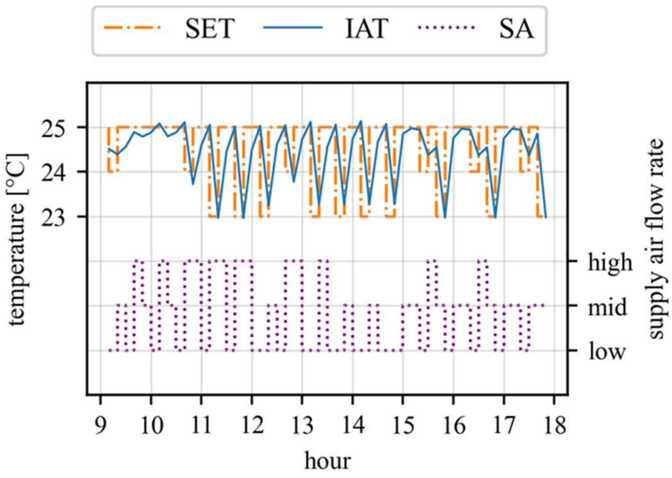
Additional analysis of the daily energy savings on the three specific days (11 May, 18 Jun, 2 Aug) was performed, and the results are presented in Figure 10. It is noteworthy that MPC intelligently adapts different control strategies depending on the cooling load patterns as follows.

(SET: Set-point air temperature [°C], IAT: Indoor air temperature [°C], SA: Supply air flow rate [L/s], refer to Table 2 for acronyms)

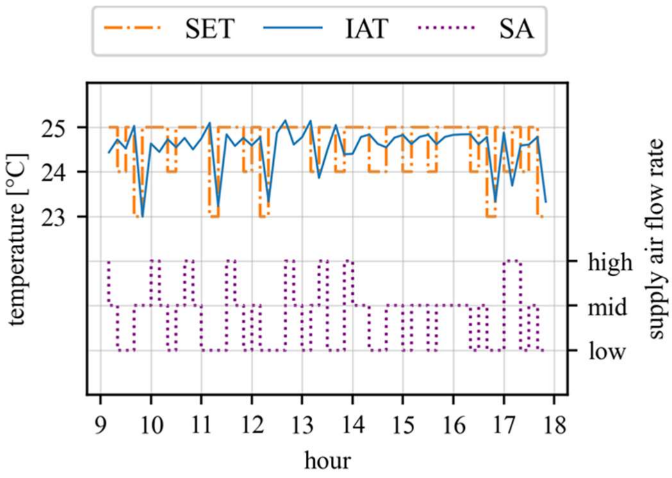
- Low cooling load day (11 May): On 11 May, MPC continuously changes SET and SA throughout the day, and thus, IAT drifts between 23°C and 25°C. Firstly, MPC takes priority to decrease IAT to the lower bound (23°C) despite a momentary high energy consumption and then keeps the VRF running on low energy consumption by having the IAT drift gradually from 23°C to 25°C (Figure 10 (a)). This 'drifting' process is repeated over the day and saves energy by 11.4%. This strategy becomes viable because 11 May is a 'low cooling load' day, and the energy saving potential by this 'drifting' would diminish as the cooling load increases.

- High cooling load day (08 Aug): On 08 Aug, when the OAT, IG, and cooling load are high (Table 4), MPC takes a different strategy, as shown in Figure 10 (c). The variations in SET and SA are relatively small throughout the day, and MPC maintains IAT close to the upper bound (25°C). The VRF runs at a constant PLR and hence, a constant COP of a high value while satisfying the temperature constraints. This 'high COP' strategy makes sense because 08 Aug is a 'high cooling load' day.

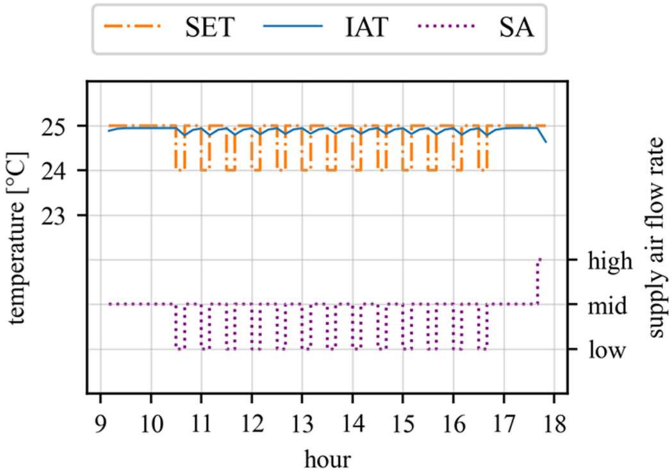
- Medium cooling load day (07 Jun): It is interesting that under a medium cooling load day, the energy savings by MPC is relatively low (Figure 10 (b)). In the morning, when the cooling load is low, MPC takes the ‘drifting’ strategy similar to Figure 10 (a), and in the afternoon, when the cooling load is high, it switches to the ‘high COP’ strategy similar to Figure 10 (c). Despite employing a combination of two strategies, the resulting energy savings are not as satisfactory.



(a) Low cooling load day (11 May)



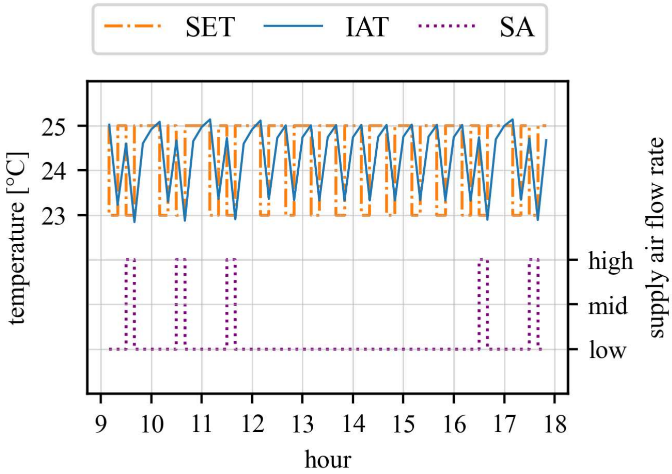
(b) Medium cooling load day (8 Jun)



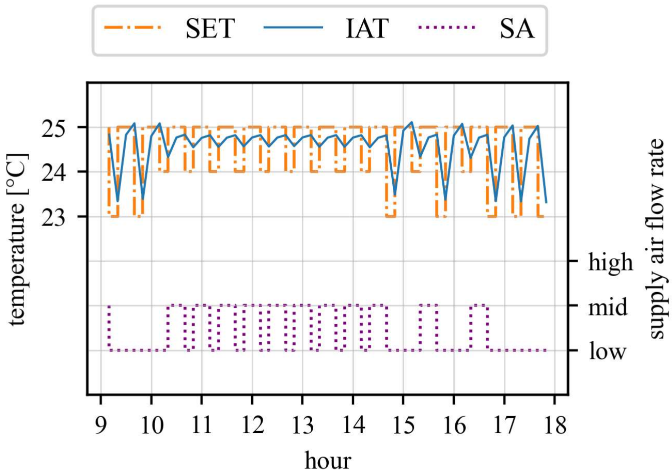
(c) High cooling load day (7 Aug)

Figure 10 Energy saving analysis of MPC (Scenario I)

Indeed, the control strategy employed by MPC can vary based on various conditions, including occupancy schedules. Figure 11 provides an energy saving analysis for Scenario II and Scenario III on the same high cooling load day (07 Aug) mentioned earlier (Figure 10 (c)), in order to demonstrate the comparison of control strategies based on occupancy schedules. In Scenario II (Figure 11 (a)), where the overall occupant density is low, the drifting strategy is utilized instead of the high COP strategy seen in Scenario I. In Scenario III (Figure 11 (b)), the control strategy varies throughout the day based on cooling load variations. In the morning and afternoon, when occupant density and solar radiation are high, the high COP strategy is employed to optimize energy consumption. However, in the evenings, as the occupant density and solar radiation decrease, the drifting strategy is implemented. Despite the same weather conditions, the cooling loads are affected by differences in occupant density and operating hours. These variations lead MPC to adapt its control strategies accordingly. This proves the flexibility and adaptability of the MPC algorithm in response to the corresponding conditions and the importance of considering occupancy schedules as well as other dynamic factors in MPC performance.



(a) Scenario II : $T_{desired}$ = 24°C, Occ 2



(b) Scenario III : $T_{desired}$ = 24°C, Occ 3

Figure 11 Energy saving analysis of MPC with different occupancy schedule

As demonstrated above, the efficient control strategy varies depending on operating conditions. Figure 12 presents a relationship curve that illustrates the correlation between the system's COP and energy consumption, with the inflection point occurring at PLR = 33%. The COP dynamics of the system must be considered in order to better understand the energy saving potential of each control strategy:

- In Section 1 (PLR < 33%): The curve exhibits a convex shape which indicates that the drifting strategy (represented by blue dotted line) is more advantageous in terms of energy consumption. A straight line connecting two arbitrary points of the curve always lies below the curve in between those points. This implies that the average energy consumption of the connected points, is lower than the average energy consumption of the constantly repeated points of the curve in between. Consequently, the drifting strategy, which operates with changing PLRs, consumes less energy compared to the high COP strategy, which operates at a constant PLR. The range of changing PLRs that satisfies the comfortable IAT range may vary at each timestep depending on the dynamic behavior of the room.

- In Section 2 (PLR > 33%): The curve takes on a concave shape which indicates that the high COP control strategy (represented by red dotted line) offers a greater advantage in terms of energy consumption. The straight line connecting two arbitrary points of the curve always exists above the curve in between. This implies that the average energy consumption of the connected points is larger than the average energy consumption of the constantly repeated points on the curve in between. Therefore, the MPC utilizes high COP strategy operating with steady PLR, unlike in section 1. By employing this strategy, IAT remains within the allowable range with minimal fluctuations, resulting in reduced energy consumption.

Due to the variations in environmental conditions, the relations between the PLR, COP, and the energy consumption changes, resulting in different optimal control strategies. This result provides insights into the energy saving potentials of the drifting strategy and the high COP strategy (Figure 13). The energy saving potentials of the drifting strategy increase as the cooling load decrease, while conversely, the energy saving potentials of the high COP strategy increase as the cooling load increase. When the cooling load is moderate, neither strategy is distinctly advantageous, so both strategies are mingled, resulting in diminished energy saving potentials.

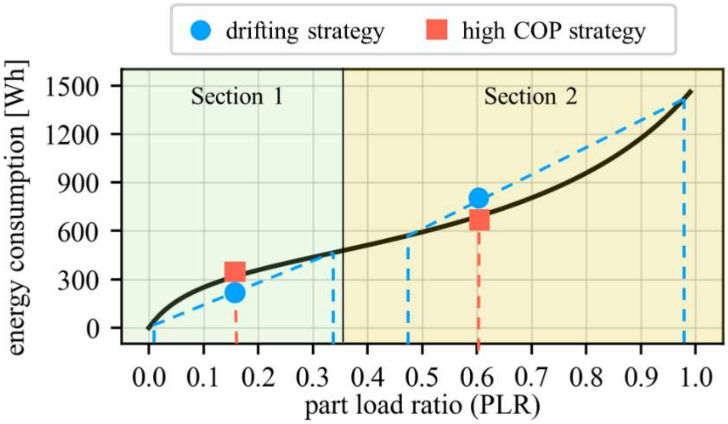


Figure 12 Control strategy analysis considering the COP of the system

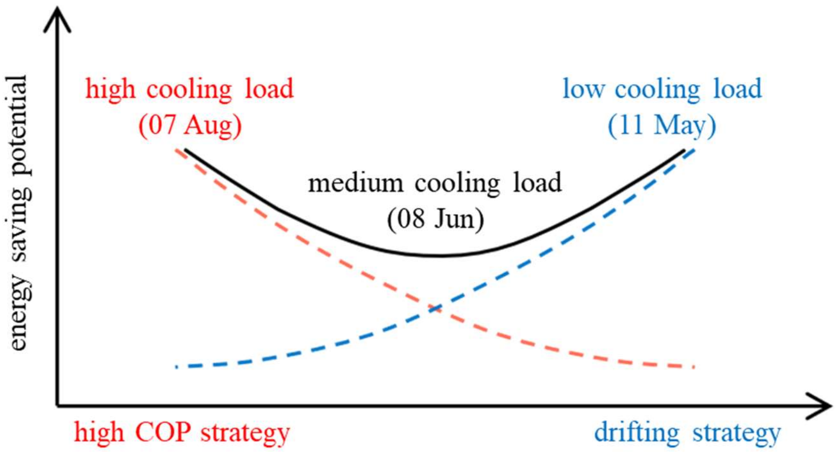


Figure 13 Energy saving potentials of the drifting strategy and the high COP strategy

Chapter 5. Conclusion

In this paper, the author presented a stochastic assessment of MPC performance of a VRF cooling system for a single-zone office space during the cooling season (01 May – 30 Sep). For this purpose, EnergyPlus was used for modeling and simulation, and two surrogate models (ANN #1, ANN #2) generated from EnergyPlus data were used for prediction. As a result, it is found that the daily energy savings by MPC can vary from 0.2% to 26.8% depending on the weather conditions, which proves to be highly stochastic. Moreover, notable variations were demonstrated in the mean values and standard deviations of MPC results between each scenario, indicating non-negligible uncertainties of MPC performance. The degree of uncertainty also differed depending on the types of variables, in that the occupancy schedule had a more significant impact than the occupant behavior.

In the process of design and assessment, numerous decisions need to be made, despite the presence of unpredictable uncertainties. In most cases, these decisions are based on deterministic rankings and numbers, assuming that one alternative will consistently outperform others. However, with the implementation of MPC, it becomes evident that the performance of a particular alternative cannot be guaranteed to be superior to others at all times due to the inherent uncertainties associated with MPC performance. This paper emphasizes the importance of considering the stochastic nature of MPC performance, as well as the performance of any HVAC system, during the assessment and decision-making processes. Merely relying on deterministic numbers without accounting for aforementioned uncertainties can result in significant performance gaps. Therefore, for objective and reproducible decision-making, uncertainty quantification must be integrated over an entire period of time with its uncertain and unknown variables considered.

Furthermore, the MPC algorithm dynamically adjusts the control strategy based on environmental conditions to optimize energy efficiency. On days with low cooling loads, MPC employs a drifting process that keeps IAT fluctuating by operating the VRF system with constantly changing PLR. Conversely, on high cooling load days, MPC intelligently adopts a high COP strategy that maximizes the COP by keeping the VRF system operating at a constant PLR. The strategies are intertwined in medium load cases, and the energy saving potentials tend to decrease when the strategies are mixed. A thorough understanding of the MPC control strategies will enable engineers and occupants to gain intuitive insights into the behaviors of the MPC and effectively implement them in real-world buildings.

One limitation of this study is the simplification of the system's COP curve to a unity curve. In reality, the COP curve exists as a surface and exhibits variations based on different operating conditions, such as outdoor air temperature. This variability makes it challenging to precisely determine when a particular control strategy becomes more efficient. It is important to be aware that these uncertainties can influence the simulation results. In the follow-up study, the authors intend to explore decision-making processes while taking into account the uncertainties of MPC performance.

References

Afram, A., & Janabi-Sharifi, F. (2014). Review of modeling methods for HVAC systems. Applied Thermal Engineering, 67(1), 507–519. https://doi.org/10.1016/j.applthermaleng.2014.03.055

Afram, A., & Janabi-Sharifi, F. (2014). Theory and Applications of HVAC Control Systems – A Review of Model Predictive Control (MPC). Building and Environment, 72, 343-355.

Afram, A., Janabi-Sharifi, F., Fung, A. S., & Raahemifar, K. (2017). Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system. Energy and Buildings, 141, 96–113. doi:10.1016/j.enbuild.2017.02.012

Afroz, Z., Shafiullah, G. M., Urmee, T., & Higgins, G. (2018). Modeling techniques used in building HVAC control systems: A review. Renewable and Sustainable Energy Reviews. doi.org/10.1016/j.rser.2017.10.044

Ahn, K., Kim, K. J., Song, K., & Park, C. S. (2020). Local vs. Integrated Control of a Variable Refrigerant Flow System Using Artificial Neural Networks. Science and Technology for the Built Environment, 26(8), 1117-1131.

Aynur, T. N. (2010). Variable Refrigerant Flow System: A Review. Energy and Buildings, 42(7), 1106-1112.

Boodi, A., Beddiar, K., Benamour, M., Amirat, Y., & Benbouzid, M. (2018). Intelligent systems for building energy and occupant comfort optimization: A state of the art review and recommendations. Energies, 11(10). doi.org/10.3390/en11102604

Cigler, J., Siroký, J., Korda, M., & Jones, C. (2013). On the selection of the most appropriate MPC problem formulation for buildings. Technical Report.

Cupeiro Figueroa, I., Cigler, J., & Helsen, L. (2018). Model predictive control formulation: A review with focus on hybrid GEOTABS buildings. Proceedings of REHVA annual meeting conference low carbon technologies in HVAC, Brussels, Belgium, 1–9.

de Wilde, P. (2014). The Gap Between Predicted and Measured Energy Performance of Buildings: A Framework for Investigation. Automation in Construction, 41, 40-49.

de Wit, M. S. (2001). Uncertainty in Predictions of Thermal comfort in Buildings (PhD thesis). Delft University, Delft, Netherlands.

del Mar, C. M., Alvarez, J. D., de A., R. F., & Berenguel, M. (2014). Comfort control in buildings. Springer-Verlag London.

Drgoňa, J., Arroyo, J., Figueroa, I. C., Blum, D., Arendt, K., Kim, D., Ollé, E. P., Oravec, J., Wetter, M., Vrabie, D. L., Helsen, L. (2020). All You Need To Know About Model Predictive Control for Buildings. Annual Reviews in Control, 50, 190-232.

DOE. (2011). U.S. buildings energy data book. Retrieved from http://buildingsdatabook.eren.doe.gov/

Gyalistras, D., Gwerder, M., Schildbach, F., Jones, C. N., Morari, M., Lehmann, B., Stauch, V. (2010). Analysis of energy savings potentials for integrated room automation. Clima - RHEVA world congress, Antalya, Turkey.

Hopfe, C. J. (2009). Uncertainty and Sensitivity Analysis in Building Performance Simulation for Decision Support and Design Optimization. PhD thesis, Technische Universiteit Eindhoven, Eindhoven, Netherlands.

Huang, G. (2011). Model predictive control of VAV zone thermal systems concerning bilinearity and gain nonlinearity. Control Engineering Practice, 19(7), 700–710. doi.org/10.1016/j.conengprac.2011.03.005.

IBPSA proceedings (2001-2021). Retrieved from www.ibpsa.org

IEA International Energy Agency and International Partnership for Energy Efficiency Cooperation. (2015). Building Energy Performance Metrics – Supporting Energy Efficiency Progress in Major Economies. Technical Report. IEA Publications.

Korean building energy standards [2022]. Retrieved from https://www.law.go.kr/

Li, H., & Wang, S. (2022). Comparative Assessment of Alternative MPC Strategies Using Real Meteorological Data and Their Enhancement for Optimal Utilization of Flexibility-Resources in Buildings. Energy, 244(A).

Liang, W., Quinte, R., Jia, X., Sun, J. Q., & Jian-Qiao, S. (2015). MPC Control for Improving Energy Efficiency of a Building Air Handler for Multi-zone VAVS. Building and Environment, 92, 256-268.

Ma, J., Qin, J., Salsbury, T., & Xu, P. (2012). Demand reduction in building energy systems based on economic model predictive control. Chemical Engineering Science, 67, 92-100.

Ma, Y., Matusko, J., & Borrelli, F. (2015). Stochastic model predictive control for building HVAC systems: Complexity and conservatism. IEEE Transactions on Control Systems Technology, 23(1), 101-116.

Macdonald, I. A. (2002). Quantifying the effects of uncertainty in building simulation (PhD thesis). University of Strathclyde, Glasgow, Scotland.

Moon, J. W., Yoon, S. H., & Kim, S. (2013). Development of an artificial neural network model-based thermal control logic for double skin envelopes in winter. Building and Environment, 61, 149-159.

Muske, K., & Badgwell, T. A. (2002). Disturbance modeling for offset-free linear model predictive control. Journal of Process Control, 12(5), 617-632.

O'Dwyer, E., De Tommasi, L., Kouramas, K., Cychowski, M., & Lightbody, G. (2017). Prioritized objectives for model predictive control of building heating systems. Control Engineering Practice, 63, 57-68.

Oldewurtel, F., Parisio, A., Jones, C. N., Gyalistras, D., Gwerder, M., Stauch, V., et al. (2012). Use of model predictive control and weather forecasts for energy-efficient building climate control. Energy and Buildings, 45, 14-27.

Picard, D., Drgona, J., Kvasnica, M., & Helsen, L. (2017). Impact of the controller model complexity on model predictive control performance for buildings. Energy and Buildings, 152, 739-751.

Rehrl, J., & Horn, M. (2011). Temperature control for HVAC systems based on exact linearization and model predictive control. In 2011 IEEE International Conference on Control Applications (CCA) (pp. 1119-1124).

Roth, K. W., Westphalen, D., Dieckmann, J., Hamilton, S. D., & Goetzler, W. (2002). Energy consumption characteristics of commercial building HVAC systems - Volume III: Energy savings potential. Technical Report.

Tian, W., Heo, Y., de Wilde, P., Li, Z., Yan, D., Park, C. S., ... Augenbroe, G. (2018). A review of uncertainty analysis in building energy assessment. Renewable and Sustainable Energy Reviews, 93, 285-301.

Yokoyama, R., Wakui, T., & Satake, R. (2009). Prediction of energy demands using neural network with model identification by global optimization. Energy Conversion and Management, 50(2), 319-327.

국문초록

건물의 기술 성능은 기후, 시나리오, 사용자 행동, 시뮬레이션 매개변수 및 수치 해석과 같은 다양한 불확실한 요소들에 영향을 받을 수 있다. 따라서, 객관적이고 재현 가능한 성능 평가를 위해서는 이러한 불확실성 요소들을 시뮬레이션 분석에 반영해야 한다.

본 연구에서는, 전 냉방기간(01 May – 30 Sep)동안 경기도 소재의 단층 사무용 건물에 대해, 가변형 냉매 유량(VRF) 냉방 시스템의 최적제어(MPC)를 수행하고, 최적제어의 성능평가를 위한 확률적인 접근을 제시하였다. 이를 위해 VRF 시스템의 에너지 소비량과 실내 온도를 예측하는 인경신경망 기반 대리모델을 구축하였다.

서로 다른 다섯 가지의 건물 사용 시나리에 따른 MPC 성능의 불확실성이 존재함을 보이고, 이를 정량화 하였다. MPC 에 의한 에너지 절감율은 기상에 따라, 0.2%부터 26.8%까지 매우 확률적으로 나타났고, 건물 스케줄과 재실자 행동을 포함한 불확실한 변수에 의해 그 불확실성이 달라짐을 알 수 있었다. 이러한 불확실성을 고려하지 않은 성능평가는 실제와의 차이를 유발하여, 의사결정의 오류를 초래할 수 있으므로, 성능평가 시 MPC 성능의 확률적인 특성을 반영해야 한다는 것을 알 수 있다.

또한, 조건에 따른 VRF 시스템의 최적제어 전략을 분석하여, MPC가 다양한 부하 조건에 따라 지능적으로 제어 전략을 바꾸며 대응하는 것을 확인하였다. 낮은 냉방 부하일에는 “drifting“전략이, 높은 냉방 부하일에는 “high COP“전략이 유리하게 작동하였고, 중간 냉방 부하일에는 두 전략이 석여 나타남을 확인하였다. 각 전략의 에너지

절감 가능성의 차이는 시스템 COP 의 동특성과 공간의 열적 거동의 상호작용을 통해 이해할 수 있다. 최적제어 전략에 대한 이해를 통해, 실제 건물에서 MPC 를 통한 효율적인 시스템 운영 및 에너지 절감에 기여할 수 있을 것으로 기대된다.

주요어 : 최적제어, 불확실성, 인공신경망, 가변형 냉매 유량 시스템, 성능평가, 제어전략, COP, 냉방

Student Number : 2021-29883