STOCHASTIC ASSESSMENT FOR MODEL PREDICTIVE CONTROL OF A VARIABLE REFRIGERANT FLOW SYSTEM

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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 0.3% to 20.4% depending on weather data. In addition, it is noteworthy that MPC intelligently takes different control strategies (high COP vs. drifting) under different weather conditions.

Keywords: model predictive control, uncertainty, artificial neural network, variable refrigerant flow system, objective performance assessment.

1 INTRODUCTION

Model predictive control (MPC) has been widely used in the building industry due to its energy saving potential. MPC determines optimal control variable(s) that minimize a cost function for a given prediction time horizon (Afram, and Janabi-Sharifi 2014). According to DOE (2015), MPC can enhance energy efficiency by up to 30% without upgrading existing appliances. 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 by 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 for a certain period of time in *a deterministic fashion*.

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 generated from EnergyPlus, two surrogated models were developed to predict energy consumption of the VRF and indoor air temperature. It will be addressed in the following sections that there is significant variation in energy savings by MPC depending on the weather data. In addition, it will be discussed that MPC itself finds optimal control strategies under different weather conditions.

2 TARGET BUILDING

The target space is a single-story office located in Seoul, South Korea (Figure 1). It consists of a single zone with a floor area of 38.5m^2 (7m × 5.5m). The space has a south-facing window and Table 1 shows the details of the target space. The thermal properties of the envelopes were selected according to Korean building energy standards (KBES) (2022). The outside boundary condition for all surfaces except the south-facing surface was set as adiabatic because this office was surrounded by identically conditioned spaces. The target office 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 of the VRF system was modeled as shown in Equation 1 that 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 2). (Figure 2).

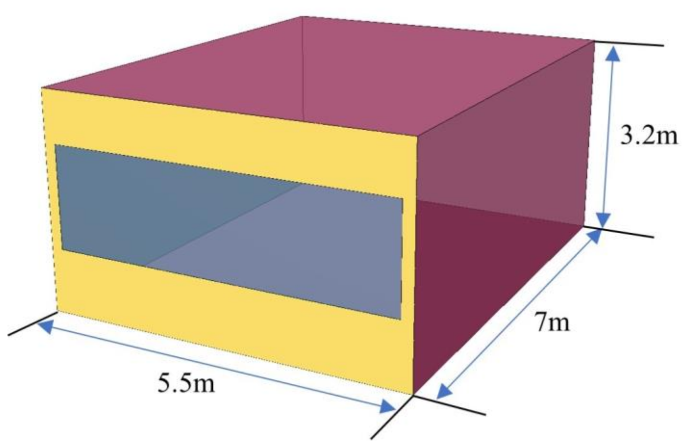

Figure 1: Target office.

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

Parameters		**Values**	
Office	Location	Seoul, South Korea	
	Total floor area [m^2]	38.5	
	Number of floors	1	
	Ceiling height [mm]	3200	
	WWR [%]	50	
	U-value [W/m^2·K]	Wall	0.15
		Window	0.9
	Fenestration SHGC	0.4	
Cooling system	Cooling capacity [W]	6,000	
	Rated COP	3.2	
Scenario	Occupant density [m^2/person]	9.0	
	Equipment density [W/m^2]	11.5	
	Lighting density [W/m^2]	8.0	
	Schedule	09:00 – 18:00	

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

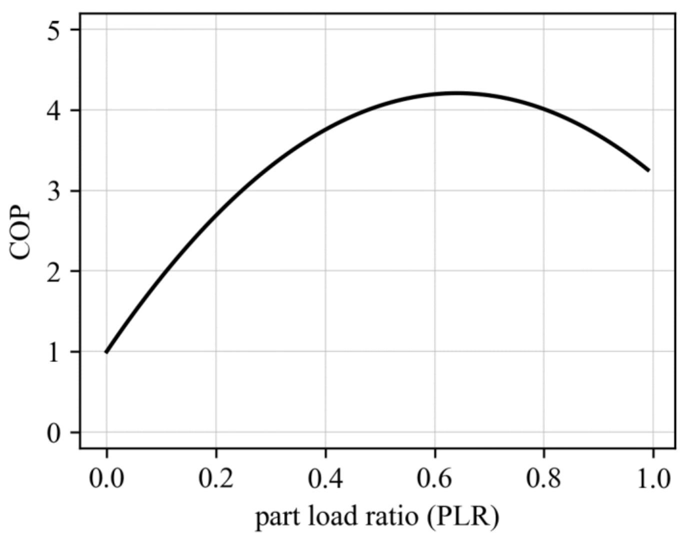

Figure 2: COP curve of VRF system in the target office.

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 later in section 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 (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 simulation from 01 May to 30 Sep. Figure 3 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 2: Inputs and outputs of ANN models.

<table>
<tr><th>Model</th><th colspan="3">Variables</th><th>Time steps</th></tr>
<tr><td rowspan="7">ANN #1</td><td rowspan="5">Inputs</td><td rowspan="3">State variables</td><td>Indoor air temperature [°C, IAT]</td><td rowspan="3">t-2
t-1
t</td></tr>
<tr><td>Outdoor air temperature [°C, OAT]</td></tr>
<tr><td>Global solar radiation incident on vertical surface [W/m^2, I_G]</td></tr>
<tr><td rowspan="2">Control variables</td><td>Set-point air temperature [°C, SET]</td><td rowspan="4">t+1
t+2
t+3</td></tr>
<tr><td>Supply air flow rate [L/s, SA]</td></tr>
<tr><td rowspan="2">Outputs</td><td colspan="2">Energy consumption by VRF and supply fan [Wh]</td></tr>
<tr><td colspan="2">Heat removal rate [W]</td></tr>
<tr><td rowspan="7">ANN #2</td><td rowspan="6">Inputs</td><td rowspan="4">State variables</td><td>Heat removal rate obtained from ANN #1 [W]</td><td rowspan="4">t-2
t-1
t</td></tr>
<tr><td>Indoor air temperature [°C, IAT]</td></tr>
<tr><td>Outdoor air temperature [°C, OAT]</td></tr>
<tr><td>Global solar radiation incident on vertical surface [W/m^2, I_G]</td></tr>
<tr><td rowspan="2">Control variables</td><td>Set-point air temperature [°C, SET]</td><td rowspan="3">t+1
t+2
t+3</td></tr>
<tr><td>Supply air flow rate [L/s, SA]</td></tr>
<tr><td>Outputs</td><td colspan="2">Indoor air temperature [°C, IAT]</td></tr>
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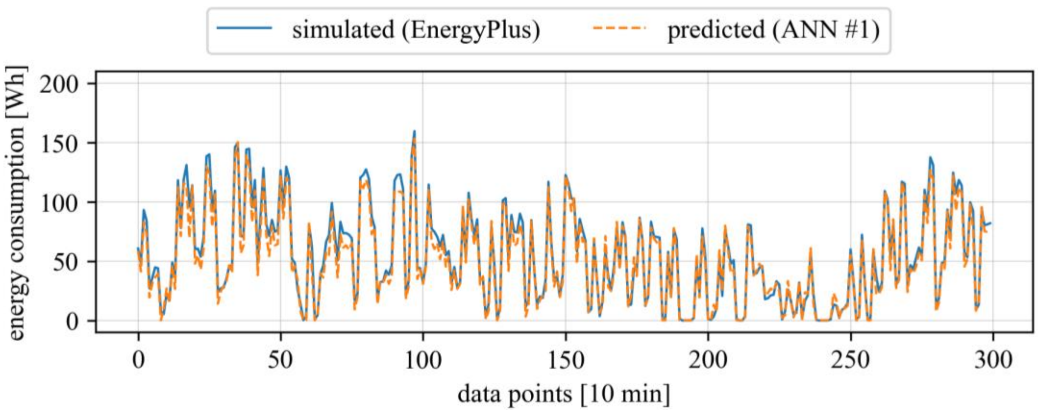
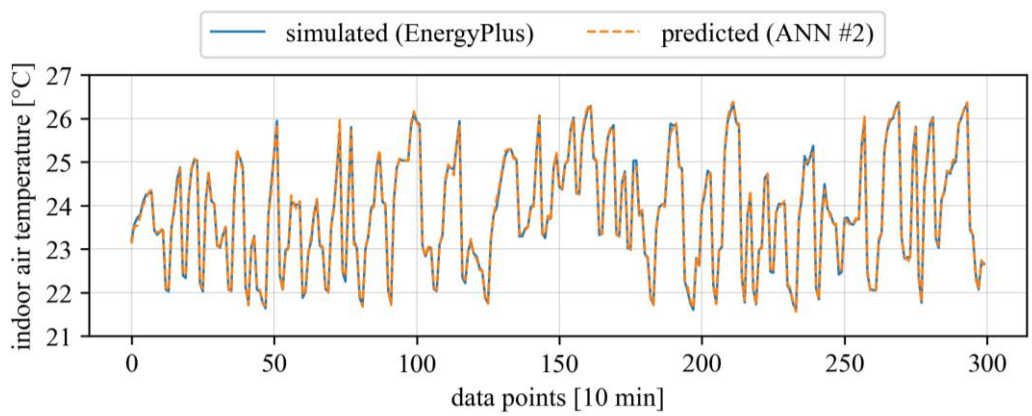


(a) VRF's energy consumption by ANN #1 (CVRMSE = 9.7%).



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

Figure 3: Comparison between simulated (EnergyPlus) vs. predicted (ANN).

4 MODEL PREDICTIVE CONTROL (MPC) RESULTS

An MPC algorithm was designed to minimize the cost function denoted by *J* (Equation 2), or energy consumption of the VRF's cooling energy over the prediction time horizon while maintaining the indoor air temperature in the range of $[\mathbf{23}℃, \mathbf{25}℃]$ as shown in Equation 2. Given three control options for the set-point air temperatures (23℃, 24℃, 25℃) and three supply air flow rates (high (230 L/s), mid (190 L/s), low (150 L/s)), the MPC algorithm exhaustively examines all possible control actions for the next three timesteps (30 minutes), resulting in $\mathbf{3 \times 3 = 9}$ control actions for each timestep and a total of $\mathbf{9^3 = 729}$ control actions for the next three timesteps.

$$\min J = \quad E_{t+1} + E_{t+2} + E_{t+3} \tag{2}$$

s.t.: $23°\mathrm{C} \leq \mathrm{IAT}_{t+1} \leq 25°\mathrm{C}$

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 (Figure 1), 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.

In order to investigate time-varying energy savings of the MPC for the entire cooling season and analyze the daily and monthly variations in the MPC performance, the simulation was carried out for the complete cooling period in South Korea (01 May – 30 Sep.). As a result, Figure 4 shows the distribution of daily energy savings of MPC. It ranges from 0.3% (28 Jul) to 20.4% (10 May) with the average of 8.0%. The standard deviation (4.6%p) is non-negligible in that it equals 57.5% of the average value. It is not surprising that the energy savings of MPC can vary significantly depending on outdoor environment (OAT, I_G). This signifies that for assessing the MPC performance, its stochastic nature must be carefully reflected. In addition, it implies that for the objective assessment of MPC performance, other uncertain variables must be considered, e.g. indoor heat generation from lights, people, and equipment, occupant schedule, infiltration/ventilation, etc.

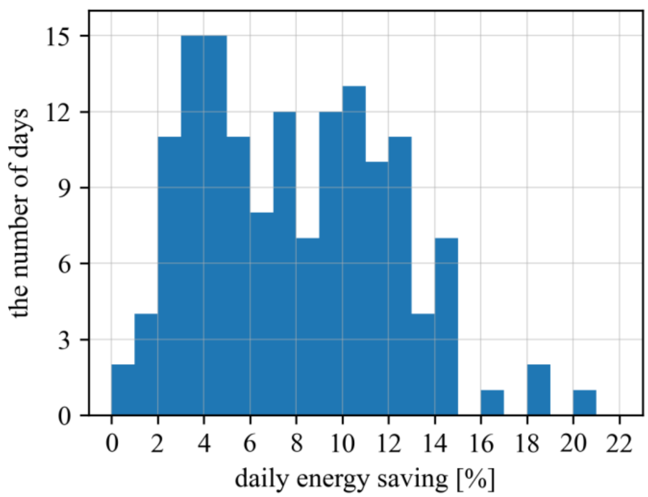


Figure 4: Daily energy savings of MPC (01 May – 30 Sep, a total of 153 days).

Figure 5 shows the relationship between the sum of hourly cooling loads and daily energy savings by MPC. The daily energy savings by MPC tends to increase as the sum of hourly cooling loads gets close to both extremes denoted by yellow and blue dots in Figure 5. Table 3 also shows environmental data on the three days (29 May, 18 Jun, 2 Aug), the sum of hourly cooling loads and energy savings by MPC.

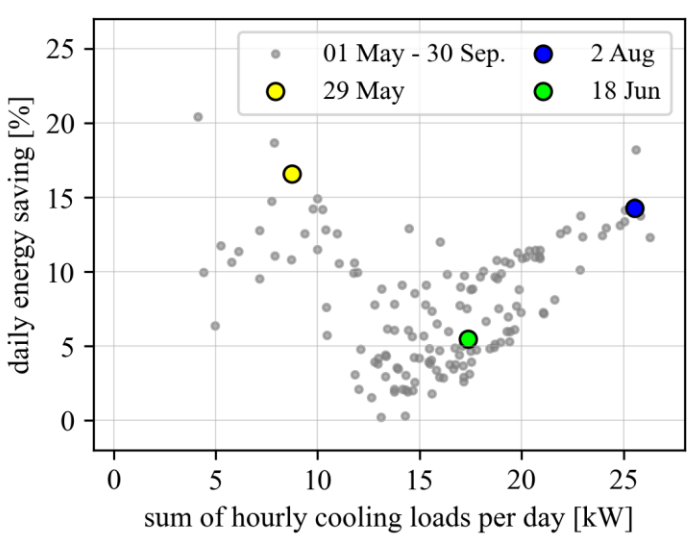


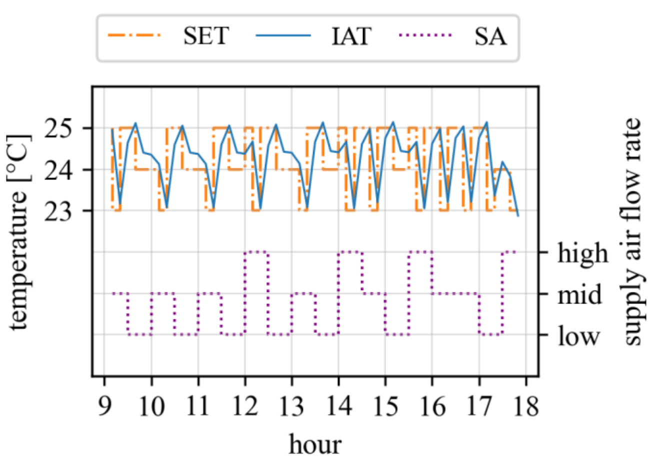
Figure 5: Daily energy savings by MPC in relation to the sum of hourly cooling loads per day.

Table 3. Outdoor environmental conditions and energy savings by MPC.

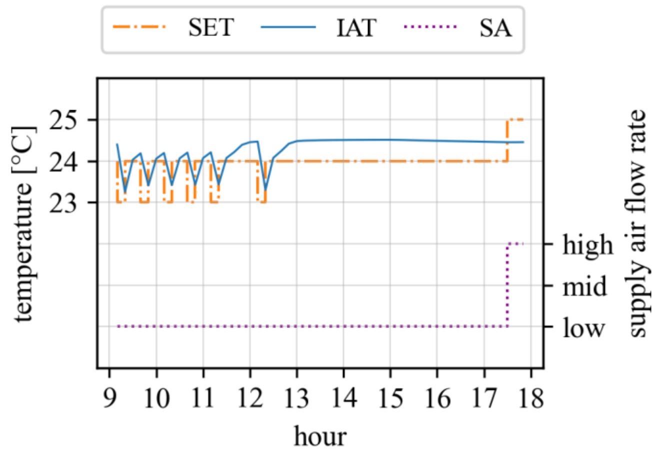
	Average OAT (‘C)	Average I_G (W/m^2)	Sum of hourly cooling loads (kW)	Energy savings by MPC
29 May	19.8	176.5	8.7	16.6 %
18 Jun	29.0	261.6	17.4	5.5 %
2 Aug	33.7	332.2	25.6	14.4 %

Further analyses of the daily energy savings on the three days (29 May, 18 Jun, 2 Aug) were conducted as shown in Figure 6. 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)

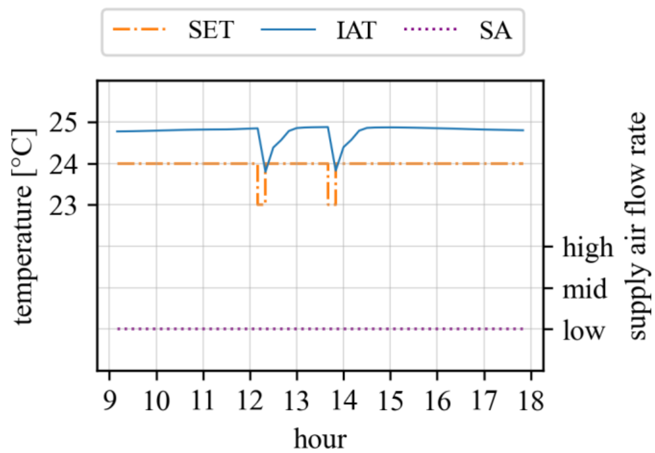
- Low cooling load day (29 May): On 29 May, MPC continuously changes SET and SA throughout the day, and thus, IAT drifts between 23°C and 25°C. Firstly, MPC takes priority to decrease IAT to the lower bound (23°C) despite a momentary high energy consumption and then keeps the VRF running on low energy consumption by having the IAT drift from 23°C to 25°C (Figure 6(a)). This control strategy becomes viable because 29 May is a ‘low cooling load’ day. This ‘drifting’ process is repeated over the day and saves energy by 16.6%. However, the energy saving potential by this ‘drifting’ would decrease as the cooling load increases.
- High cooling load day (2 Aug): when the OAT, $I_{G,}$ and cooling load are high (Table 3), MPC takes a different strategy as shown in Figure 6(c). MPC maintains IAT close to the upper bound (25°C). Throughout the day (2 Aug), the VRF runs at a PLR of about 0.6, operating with a high COP of about 4.0 (Figure 2). This ‘high COP’ strategy (PLR = 0.6) makes sense because Aug 2 is a ‘high cooling load’ day.
- Medium cooling load day (18 Jun): it is interesting that under a medium cooling load day (18 Jun), the energy savings by MPC is low (Figure 6(b)). In the morning, MPC takes the ‘drifting’ strategy similar to Figure 6(a) and in the afternoon, it takes the ‘high COP’ strategy similar to Figure 6(c), but the energy saving result is not satisfactory. It can be inferred that as shown in Figure 7, the ‘high COP’ and ‘drifting’ strategies are mingled on the medium cooling load day and thus, energy saving potentials are decreased.



(a) Low cooling load day (29 May).



(b) Medium cooling load day (18 Jun).



(c) High cooling load day (2 Aug).

Figure 6: Energy saving analysis of MPC.

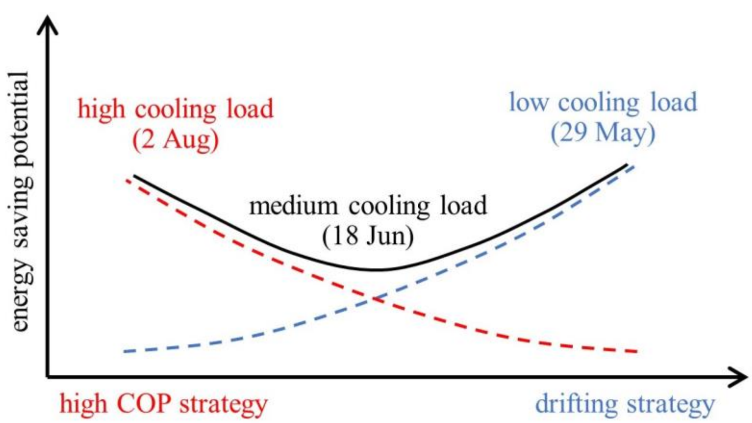


Figure 7: Different control strategies under low, medium and high cooling load days.

5 CONCLUSION

In this paper, the authors 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 to generate two surrogate models (ANN #1, ANN #2). As a result, it is found that the daily energy savings by MPC can vary from 0.3% to 20.4% which proves to be highly stochastic. In addition, on a high cooling load day, MPC intelligently takes a *high COP* strategy while MPC repeats the *drifting* process on a low cooling load day.

This paper suggests that when assessing the VRF performance as well as any other HVAC system performance, the aforementioned stochastic characteristics must be carefully reflected. In other words, for objective and reproducible performance assessment, uncertainty quantification must be integrated over an entire period of time. As indicated in Section 4, decision-making without taking the stochastic nature into account may lead to a significant performance gap.

The limitation of this study is that MPC performance analysis was conducted only under varying weather conditions (OAT, I_G). In the follow-up study, the impact of other uncertain parameters, e.g. thermal properties, internal heat generation, occupant behavior, etc. on the MPC performance will be included.

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REFERENCES

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

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

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

De Wilde, P., 2014. "The Gap Between Predicted and Measured Energy Performance of Buildings: A Framework for Investigation". *Automation in Construction* vol.41, pp.40-49

De Wit, M.S., 2001. *Uncertainty in Predictions of Thermal comfort in Buildings*. PhD thesis, Delft University, Delft. Netherlands

DOE. 2015. Chapter 5: Increasing Efficiency of Building Systems and Technologies. QUADRENNIAL TECHNOLOGY REVIEW: An Assessment of Energy Technologies and Research Opportunities.

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

IBPSA proceedings (2001-2021), 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], https://www.law.go.kr/

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

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

Ma, J., J. Qin, T. Salsbury, and P. Xu. 2012. "Demand Reduction in Building Energy Systems Based on Economic Model Predictive Control". *Chemical Engineering Science* vol.67, pp.92-100.

Ma. Y., J. Matusko, and F. Borrelli. 2015. "Stochastic Model Predictive Control for Building HVAC Systems: Complexity and Conservatism. *IEEE Transactions on Control Systems Technology* vol.23 (1), pp. 101-116.

Macdonald, I.A., 2002. *Quantifying the Effects of Uncertainty in Building Simulation*. PhD thesis. University of Strathclyde. Glasgow, Scotland

Moon, J. W., S. H. Yoon, and S. Kim. 2013. "Development of an Artificial Neural Network Model Based Thermal Control Logic for Double Skin Envelopes in Winter". *Building and Environment* vol.61, pp.149-159.

Tian, W., Y. Heo, P. de Wilde, Z. Li, D. Yan, C. S. Park, X. Feng, and G. Augenbroe. 2018. "A Review of Uncertainty Analysis in Building Energy Assessment". *Renewable and Sustainable Energy Reviews* vol.93, pp.285-301.

Yokoyama, R., T. Wakui, and R. Satake. 2009. "Prediction of Energy Demands Using Neural Network with Model Identification by Global Optimization". *Energy Conversion and Management* vol.50 (2), pp.319-327.

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