Exploring the use of TABS and Peak-Shift Control in Office Buildings

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ABSTRACT
Thermally activated building systems (TABS) are gaining attention as a means of realizing comfort and energy efficiency in office spaces. TABS use the building mass for heat dissipation and the storage part of the building to save energy, improve comfort, and shift peak energy consumption. However, the thermal response is slow due to the large thermal capacity. Therefore, in this study, we propose a method for optimizing the operation of TABS by applying Adaptive Model Predictive Control (AMPC) combined with sequential updating of the predictive model through online estimation. Furthermore, we verify the feasibility of Demand-Response (DR) implementation using the proposed method. From the results, AMPC was shown to reduce the control error compared to MPC and to reduce computational load compared to Nonlinear MPC (NLMPC). We also confirmed that DR control using AMPC can suppress TABS operation during the hours of 8:00 - 10:00 and 16:00 - 18:00 when electricity demand is high, while maintaining PMV within ±0.3 and ensuring energy efficiency.

KEYWORDS
TABS, MPC, IDEAS, DR, thermal storage, online estimation

1 INTRODUCTION
In recent years, thermally activated building systems (TABS), which use the structure of a building to dissipate or store heat, have been attracting attention as a means for achieving a thermal environment that realizes both comfort and energy savings in office spaces. TABS are expected to offer a variety of advantages, including high comfort, energy savings, and shifting peak energy consumption, by utilizing the high thermal capacity of the building. However, high thermal capacity means slow thermal response, making it desirable to introduce dynamic control methods. In a previous study[1), 2)], we proposed a method for optimizing model predictive control (MPC) by combining load forecasting with machine learning. The method however leaves room for further study, such as shifting peak electricity demand through heat storage and improving control performance using nonlinear MPC (NLMPC)[3), 4)]. Because the thermal response of TABS is nonlinear, when the nonlinear predictive model is used for NLMPC, high controllability can be expected for complex behaviour of the controlled object as well as a reference is needed here. However, the nonlinear model has various limitations, including the need for a large amount of training data, the time required to model the target system, and the difficulty of obtaining a solution within the sampling time for large and computationally demanding systems.

Therefore, we propose adaptive MPC (AMPC)[5, 6)] as a control method for TABS, specifically by combining sequential updating of the predictive model with online estimation. Using this method, the possibility of individual TABS control and DR control with TABS is verified through a co-simulation with Dymola and MATLAB/Simulink (Figure 1). In addition, comparative verification between AMPC, regular MPC and NLMPC will also be performed.

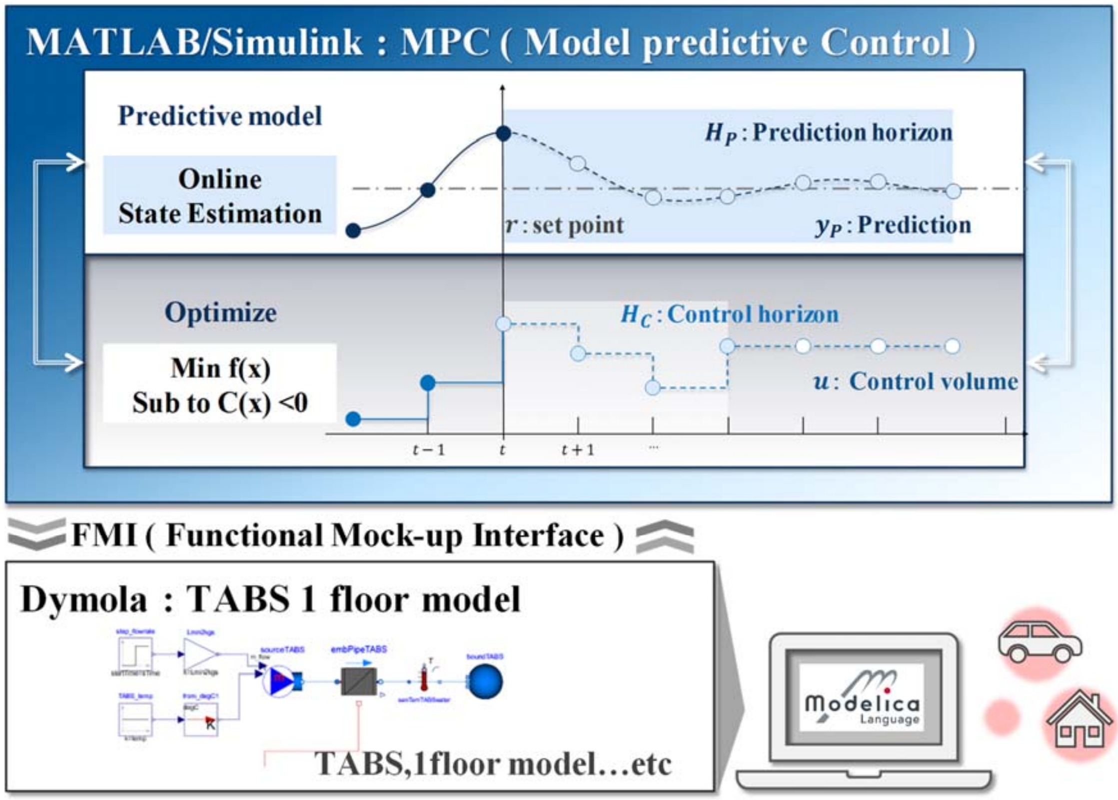

Figure 1: Outline of this study

2 ANALYSIS OVERVIEW

2.1 Overview of control methods

In this study, MPC-based control is performed on TABS. MPC is a control method that sequentially determines the optimal level of operation at the current time while predicting future response. However, since it is necessary to predict the future behaviour of the controlled variable at each sample time, the prediction model that expresses the dynamic causal relationship between the manipulated variable and the controlled variable is required. On the other hand, the thermal behaviour of TABS (changes in ceiling surface temperature and room temperature) is a nonlinear phenomenon. So, when using MPC to operate TABS, NLMPC with the nonlinear prediction model could be implemented. However, when modelling large nonlinear systems, the complexity of the optimization problem is a concern due to the consideration of model parameters and the huge amount of training data required. In contrast, AMPC sequentially updates the parameters of the linear prediction model online by using the input/output data at each time. AMPC has some advantages: the modelling is possible even in the absence of prior data, the computational load is low, and the system can cope with unexpected disturbances. Therefore, in this study, MPC, NLMPC, and AMPC are verified as control methods for TABS, with the transfer function (TF)[7)] model, the nonlinear auto regressive exogeneous (NLARX)[8)], and the recursive ARX (RARX)[9)] model used as the respective prediction models. The TF model represents the relationship between the input data and output data of the controlled by object. In this study, The TF model is identified from the step response with the TABS operation amount (water-supply flow rate). The TABS operation amount is used as the input data and the ceiling surface temperature is used as the output data. It is then converted into a state-space representation and used as a dynamical model for MPC. The NLARX model is also extension of the linear ARX model to the nonlinear case. The linear ARX model is a model that incrementally linearly predicts the variable to be forecast from its own historical time series data of other external input variables. The RARX model is the linear ARX model that is sequentially updated from the input/output data of the control target. In this study, the sequential least squares method is applied as the estimation method. A Kalman Filter (KF) is employed as the online model parameter estimation algorithm in this study.

2.2 Analysis model

Figure 2 shows the model of the analyzed floor. The analysis target is a one-floor model[2] of TABS created in Dymola[10], a modelica-based[11] composite physical-modelling tool. In this study, the target heating, ventilation, and air conditioning system and the building model were constructed using IDEAS[12].

2.3 Analysis conditions

Tables 1 and 2 show the Dymola and MPC analysis conditions. The analysis period was assumed to be August and the duration was 1 week each for the initialization period and the primary analysis. In the Dymola model, the schedules of occupancy are given according to the loading schedule shown in Figure 3. Specifically, the loads of Light and OA (office automation) shown in Figure 3 were predicted by the random forest model, while state estimation was performed using the KF. The target value of the ceiling surface temperature was analysed by Dymola in advance and set to 24.5°C ± 0.3°C, which is considered to be within the comfort zone. The required ventilation air volume (480m^3/h) is treated by a desiccant outside air handling unit and then supplied by a floor outlet ventilation system.

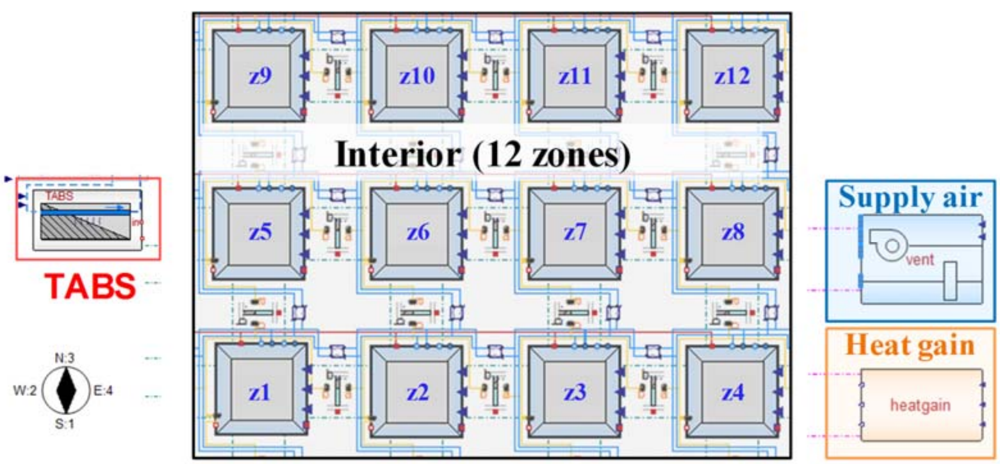

Figure 2: Analysis model (1 floor)

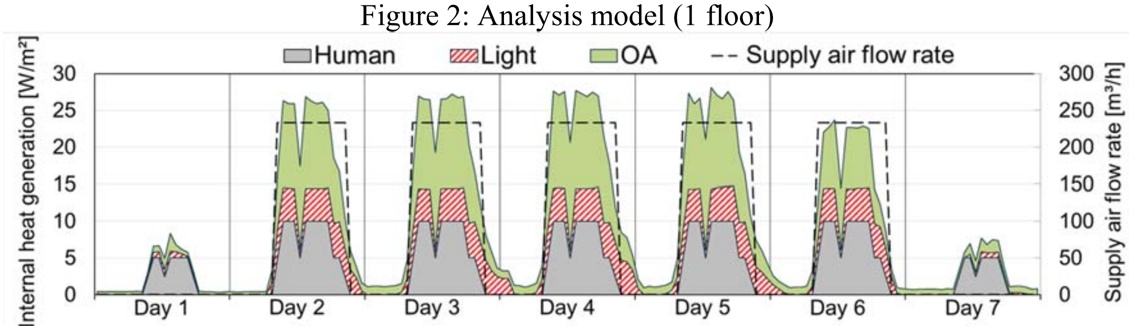

Figure 3: The loading schedule

Tables 1: Analysis conditions of Dymola

Weather data		Tokyo, Japan[13)]
TABS	Water supply, Temperature	5L/min, 16℃
Ventilation	Flow rate, Supply temperature	30m³/h・person, 23℃
Heat generation	Human	$10W/m^2$
	OA	$15W/m^2$
	Lighting	$5W/m^2$
Boundary condition under the ceiling and floor		23℃

Tables 2: Analysis conditions of MPC

Predictive Model		TF, NLARX, RARX
Algorithm		Effective Constraint Solver (KWIK)
Sample time		1step = 3,600s
Prediction horizon		24step
Heat generation		Predicted by RF, KF
Constraints	u [L/min]	$0 \leq u \leq 5$
	Δu [L/min]	$-5 \leq \Delta u \leq 5$
	y [°C]	$24.2 \leq y \leq 24.8$ (Weekday Work Hours)

2.4 Cases

Table 3 shows the details of the anayzed cases: in Case 1, comparative verification of control performance is performed using MPC, NLMPC, and AMPC; in Case 2, optimal control is performed by AMPC and DR-AMPC, with constraints on the ceiling surface temperature during weekday occupancy in consideration of the actual operation. In all cases, on/off control was used during the initialization period.

Tables 3: Analysis case

Case	comparison items	control method	cost function	constraint
Case1-1	Control performance	MPC	Minimize temperature error	-
Case1-2		NLMPC		
Case1-3		AMPC		
Case2-1	Energy saving performance	AMPC	Minimize water supply flow rate	Office hour: 24.5°C ± 0.3°C
Case2-2		DR-AMPC		Office hour: 24.5°C ± 0.3°C Water supply restrictions during times of increased demand (8:00 - 10:00, 16:00 - 18:00)

3 ANALYSIS RESULTS

3.1 Case1: Control performance verification

Figure 4 shows the root mean square error of the ceiling surface temperatures and the target for each zone in Case 1. In Case 1-1, the error variation is large, while in Case 1-2, the control error is smaller. Case 1-3 resulted in a slight increase in control error compared with Case 1-2 but had a higher accuracy compared with Case1-1. The computation time for NLMPC and AMPC was about 49.3 and 33.1 times longer than MPC, respectively. AMPC reduced the computation time by 32.8% compared with NLMPC. Therefore, this study examined DR control considering the actual operation with AMPC applied to reduce the computational load.

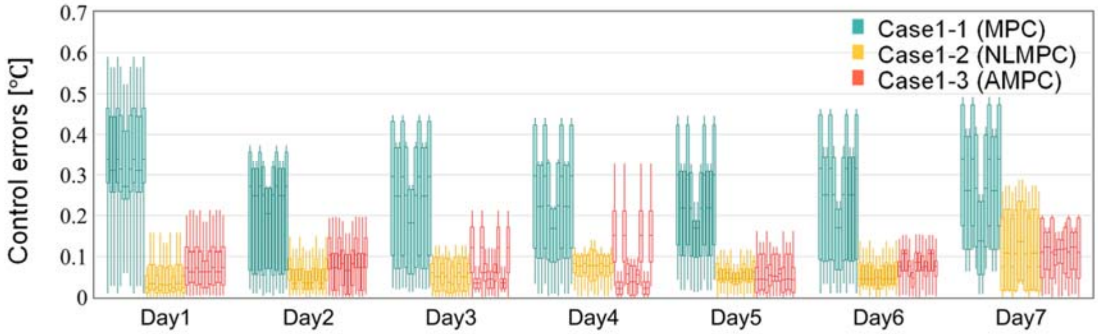

Figure 4: RMSE of the ceiling surface temperatures and the target in Case 1

3.2 Case2: Verification of DR methods

Figures 5 and 6 show the time variations of the ceiling surface temperature and water flow rate, respectively, for Case 2. In all cases, the control satisfied the constraint conditions. Figure 6 also shows that in Case 2-2, the water supply was restricted during high-demand hours (8:00–10 and 16:00–18:00) in consideration of DR, which resulted in a reduction in water supply during certain hours. The right side of Figure 6 shows the percentage of the total weekly water supply flow for Case2-1and Case2-2 when Case 1-1 was set as 100%. It shows that the water supply flow rate is approximately 95%, which means that the water supply flow rates were generally the same before and after implementing DR control. Figure 7 shows the time variation of PMV in Case 2. The PMV values of all cases were generally 0.00–0.25, indicating that comfort was maintained. From the above results, it was confirmed that employing AMPC for one floor of a typical office with TABS installed enables TABS operation considering DR while maintaining energy savings and comfort.

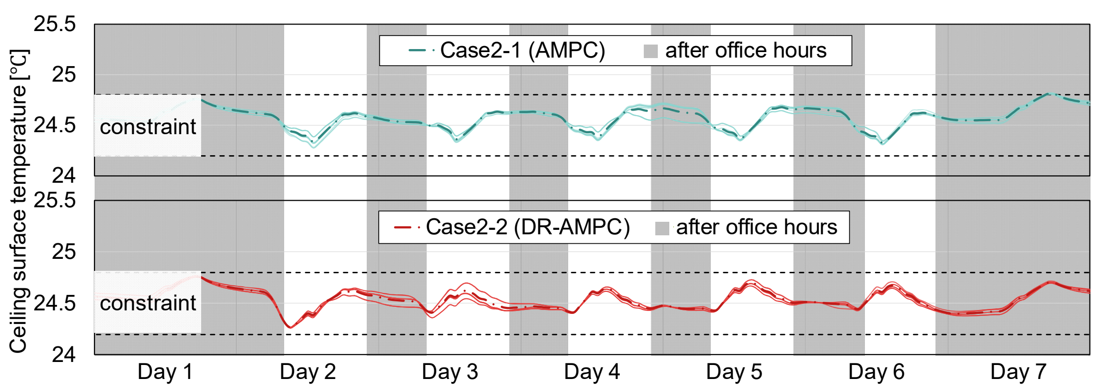

Figure 5: Change over time of the ceiling surface temperature in Case 2

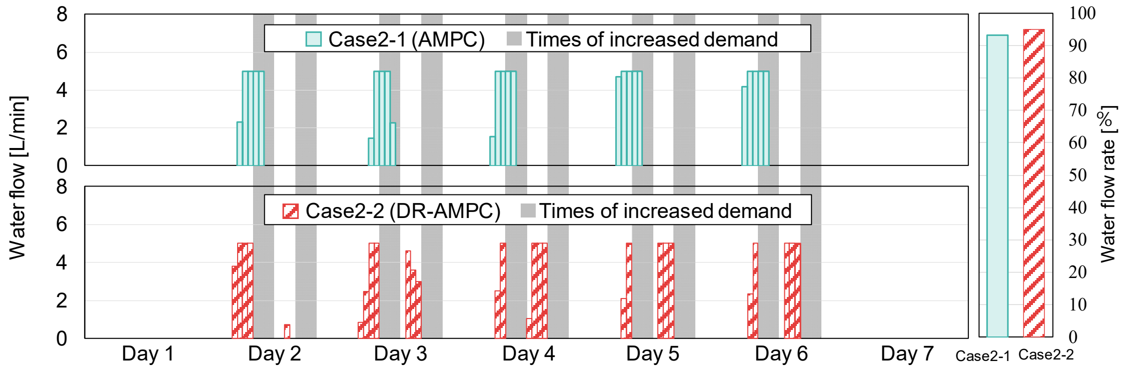

Figure 6: Change over time of the water flow rate in Case 2

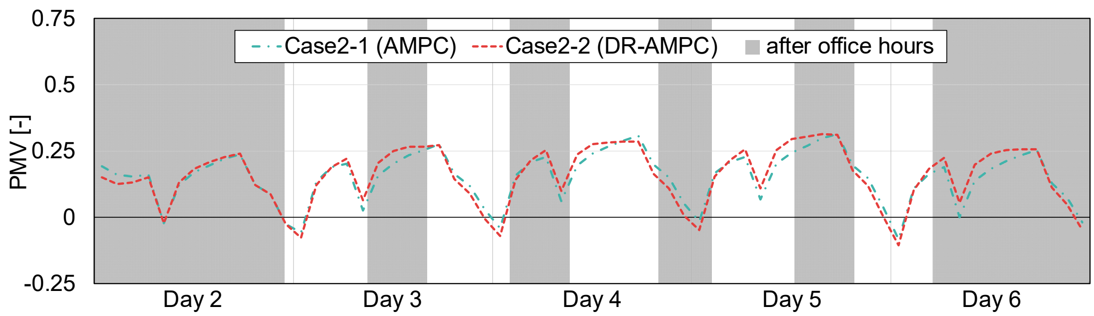

Figure 7: Change over time of PMV in Case 2

4 CONCLUSIONS

In this study, comparative verification of MPC, NLMPC, and AMPC for TABS was performed to assess control and energy savings, computational load, and DR control. As a result, we confirmed that DR control using AMPC enables DR-aware TABS operation while maintaining energy savings and comfort. AMPC also reduced the computational load by 32.8% compared with NLMPC while reducing the control error by about 66.7%compared with MPC. Verification of simulation results by comparison with actual measurement results is a future challenge.

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