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Multi-Model Predictive Control on HVAC Chilled Water Pump for Temperature Control and Energy Consumption Reduction for Auditorium

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MUHAMMAD AFIFF RIZKI, ARIES SUBIANTORO

Department of Electrical Engineering, University of Indonesia, Depok, Indonesia
Email: aries.subiantoro@ui.ac.id

ABSTRAK

Sebagian besar konsumsi energi berasal dari tingginya permintaan dari bangunan, dimana sebagian besar berasal dari sistem HVAC (Heating, Ventilation, dan Air Conditioning). Strategi kendali optimal diperlukan untuk penghematan energi. Tulisan ini mengusulkan strategi kendali multi-model MPC (Model Predictive Control) untuk mengendalikan pompa air dingin HVAC untuk mengurangi konsumsi energi pada auditorium gedung MAC (Makara Art Center) UI. Model bangunan dimodelkan dalam perangkat lunak EnergyPlus, sedangkan strategi kendali dimodelkan menggunakan MATLAB, dimana kedua software akan berkomunikasi melalui BCVTB (Building Control Virtual Test Bed). Kinerja kendali yang dikembangkan telah diuji dalam kondisi operasi yang berbeda dan serangkaian perubahan suhu yang berbeda. Hasilnya menunjukkan bahwa pengendali yang diajukan dapat menurunkan konsumsi energi pompa air dingin sebesar 13,1% dibandingkan dengan pengendali On/Off yang sudah ada.

***Kata kunci**: BCVTB, HVAC, Kendali Optimal, MPC, Pompa Air Dingin.*

ABSTRACT

Most energy consumption comes from the high demand from buildings. A large portion from buildings comes from the HVAC systems. A proper optimal control strategy is needed for energy savings. This paper proposes a multi-model MPC strategy for controlling the chilled water pump HVAC to reduce energy consumption for an auditorium in MAC UI building. The building model is modeled in EnergyPlus software, while the control strategy is modeled using MATLAB where both software communicates using BCVTB. The developed control performance has been tested under different operating conditions and different set of temperature changes. The result shows that the proposed controller can reduce the total energy consumption of chilled water pump by 13.1% compared to the existing On/Off controller.

***Keywords**: BCVTB, Chilled Water Pump, HVAC, MPC, Optimal Control.*

1. INTRODUCTION

Buildings require the most total electricity energy consumption, from 40-42% in western countries **(Morales et al., 2020)**. This energy feeds lights, electronic equipments, security systems, and mostly HVAC. When the global temperature increases due to greenhouse emmisions, HVAC systems contributes a significant amount from the energy consumptions where it can go up to 60% of the total energy in a building **(Cong et al., 2024)**. In the United States alone, 7% of all greenhouse emissions are caused by HVAC systems and most commercial buildings have not yet implemented HVAC control at scale **(Henze et al., 2024)**. Therefore, it is better to find methods to reduce the energy consumption in HVAC systems **(Homod, 2018)**.

Maintaining the desired temperature of a room needs a controller that controls the signal to the HVAC. The most commonly used control for HVAC is none other than the On/Off controller with constant single speed **(Nishijima, 2016)(Ziabari et al., 2017)**. This type of control needs a high starting current, which leads to higher energy consumption **(Anil et al., 2023)**. Modern control methods used in HVAC systems while providing temperature comfort can save up to 30% in energy costs compared to On/Off control **(Homod, 2018)(Valenzuela et al., 2020)**.

Over the last decade, there has been various modern control development for HVAC systems. Morales uses fuzzy logic-based driven control for HVAC sysstems can improve 32% from signal input over conventional control **(Morales et al., 2020)**. Another two popular controls used for HVAC systems are MPC and RLC (Reinforced Learning Control), which can expect to reduce emissions and costs by 15-25% compared to conventional PID control **(Henze et al., 2024)(Yang et al., 2022)**. Mantovani uses reference tracking techniques, reducing 15% of the total cost for temperature control of a building **(Mantovani et al., 2015)**. With all the various controller developments stated above, requiring a modern control method for HVAC systems will lead to cost savings and energy efficiency while maintaining comfort **(Leon, 2025)**. These control developments over HVAC above is mainy focused on fan control compressor operation, which consume the largest portion of energy **(Fons et al., 2024)**. However, the operation for the chilled water pump also contributes a significiant amount of energy consumption **(Wijaya et al., 2022)**. Hence, this paper focuses on the control for the chilled water pump.

The main objective for this research is to create an optimal control for the HVAC chilled water pump for the auditorium in MAC building in University of Indonesia. The past study made by Kelvin uses artificial neural network (ANN) to control the the water pump **(Wijaya et al., 2022)**, this type of control uses a black box model which is difficult to understand the working of the sytem and not able to add input and output coinstraints, hence this paper propose of using multi-model MPC as a controller to eliminate the problem setated using ANN. This type of model can represent the nonlinear behaviour of the system while being able to create a multi input and multi output system **(Lestanto et al., 2017)**. The problem statement is that the existing controller is still using the conventional On/Off controller. Using EnergyPlus as a model can act as a simulator for the building and predict the total energy consumption accurately **(Eid et al., 2024)(Radecki et al., 2017)**. With the help of BCVTB software, it can simulate the building model in EnergyPlus with the controller in MATLAB to run simultaneously and exchange datas. The proposed method is expected to improve the input signal for the chilled water pump and reduce costs compared to the existing controller while maintaining a level of comfort based on ASHRAE-55-2010 standards for different temperature set points.

2. SIMULATION ESSENTIALS

2.1 *Research Flowchart*

The research consist of 3 main components, these are building model in EnergyPlus software, identification model for MPC controller, and the controller itself coded in MATLAB. The research starts with building the model in EnergyPlus software, then a model for the multi-model MPC is created for the identification, this identification stops after the model is validated with at least 10% of the FOE (Final Output Error) shown in Equation (2, finally develop the MPC controller and simuate to see the performance and compare with the exising controller. These steps can be shown in a flowchart in Figure 1.

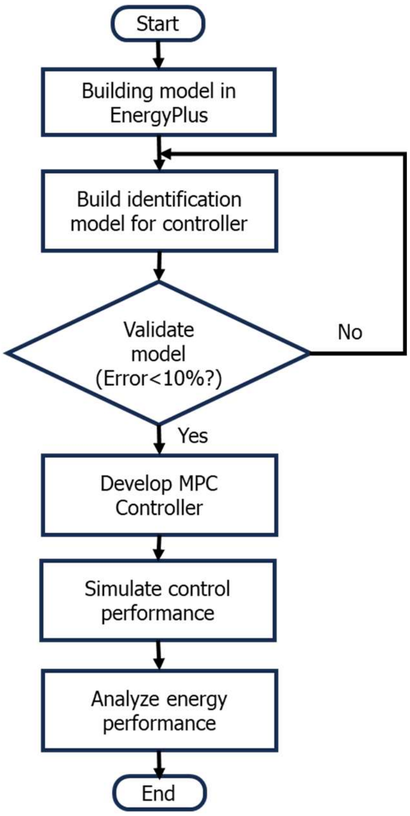


Figure 1. Multi-Model MPC Research Flowchart for Chilled Water Pump

EnergyPlus software is an energy and thermal load simulation program based on user's description of a building from its physical material, mechanical systems, evironments, ect. **(U.S Department of Energy, 2019)**. This software is able to simulate different HVAC configurations and various output results. Using the existing building model in EnergyPlus from previous works **(Wijaya et al., 2022)**, the problem would only be creating the model for the controller and the controller itself.

Creating a model for multi-model MPC needs three parameters, namely input, state, and output **(Lestanto et al., 2017)**. The input for the simulation will be the flow rate of the chilled water pump ($\dot{m}_{flow}$), the output will be the desired room temperature (T_r), but the state can vary depends on the the requirement for the building model. Hence, there needs to be a validation for the model by finding the sum of squared error (J_{ee}) shown in Equation (1 and the FOE shown in Equation (2. After finding the best model for the system, we then develop an MPC controller with various different parameters to analyze the energy performance compared to the existing On/Off control.

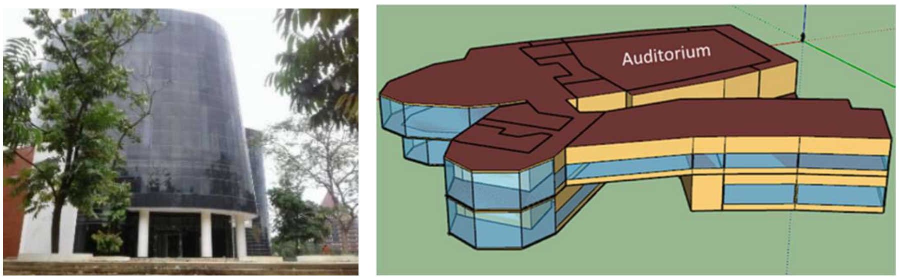
$$J_{ee} = \frac{1}{N}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2 \quad (1)$$

$$FOE = \frac{1}{N}\frac{N+m}{N-m}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2 \quad (2)$$

Where N is the number of samples, m is the number of element matrix used, y is the output, and $\hat{y}$ is the estimated output.

2.2 Building Model

The building model for the object for the study is a campus building of MAC in University of Indonesia. The actual building is shown in Figure 2(a), whearas Figure 2(b) shows building configuration for simulation in EnergyPlus, it is noted that the model lacks detail such as doors and furnitures to simplify the simulation while providing accurate model to the actual building. The building has an area of 2400 m^2, a ceiling of 4-5 m, and approximately a window to wall ratio (WWR) of 40%. The building model in EnergyPlus separates into 9 zones, this includes the auditorium which is the main focus object for this research.



(a) (b)

Figure 2. (a) Actual MAC Building; (b) Simulation Model Design

Table 1. Material Characteristics for MAC Building Simulation

Construction	Materials	Thermal Conductivity W/(m.K)	Thermal Resistance (m^2.K)/W
Interior Ceiling	100 mm Lightweight Concrete	0.53	
	Ceiling Air Space Resistance		0.18
	Acoustic Tiles	0.06	
Interior Wall	19 mm Gypsum Board	0.16	
	Wall Air Space Resistance		0.15
Interior Floor	Acoustic Tiles	0.06	
	Air Space Resistance		0.18
	100 mm Lightweight Concrete	0.53	
	Carpet Pad		0.1
Interior Partition	25 mm Wood	0.15	
Interior Window	Clear 3 mm	0.9	
Exterior Window	Theoritical Glass	0.0133	
Interior Door Roof	25 mm wood	0.15	
	Roof Membrane	0.16	
	Roof Insulation	0.049	
	Metal Decking	45.006	
Exterior Wall	1 in. Stucco	0.69	
	8 in. Concrete HW	0.17	
	Wall Insulation	0.08	
	½ Inch Gypsum	0.16	

Table 1 shows the specification of the material for building and construction for MAC building, these material include the types of the ceiling, wall, and roof with its thermal charactersitics such as thermal conductivity and thermal resistance. Table 2 shows the chiller specification for the audiorium room, it is an air cooled chiller designed for a large room with a high rated of cooling capacity. This chiller is only connected to the auditorium room, so it does not influence other zones for the building.

Table 2. HVAC Chiller Specification for MAC Auditorium

Construction	Materials
Condenser type	Air Cooled
Rated cooling capacity	196 kW
Chiller rated COP	4
Primary chilled water pump rated head	179352 Pa
Design pump power consumption	2468 W
Average water mass flow rate	9.66 g/s
Chilled water design set point	6.67 ◦C
Condenser water design set point	29.4 ◦C
Supply fan delta pressure	75 Pa
Supply fan total efficiency	75 %
Supply fan motor efficiency	90 %
Outdoor air flow rate per person	0.0094 m^3/s

2.3 Co-simulation

Figure 3 shows the architecture for the simulation. There are three types of program used in the simulation, namely BCVTB, EnergyPlus, and MATLAB. Both EnergyPlus and MATLAB acts as an actor in BCVTB program, it is shown that BCVTB acts as a mediator between the other two programs, this allows to execute the simulation simultaneously without opening each individual programs manually. BCVTB is a program developed based on Ptolemy II software environment capable to connect individual programs to exchange data simultaneously **(BCVTB, 2016)**.

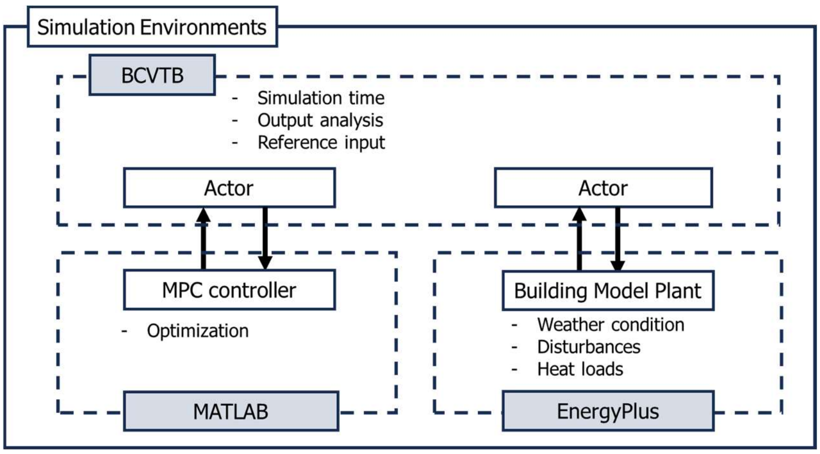


Figure 3. Co-simulation Diagram for Multi-Model MPC for Chilled Water Pump using BCVTB

This software will become the main program for the simulation by defining the simulation time, times step, reference input, and scopes for further analysis. Building model in EnergyPlus aquires the input information in BCVTB via ExternalInterface, then simulates the model in a timestep and hand the output back to BCVTB. The MPC controller on the other hand is computed using MATLAB software, where it does the optimization problem based on the inputs given from the output from building model and reference.

2.4 Multi-Stage System Identification

This multi-stage identification will be used as a model in the multi-model MPC. This identification can represent the nonliear behaviour of the system in a combination of a state space model **(Lestanto et al., 2017)**. The purpose of system identification is to find out all the matrix parameters that can represent the system. The state equation for the first stage is represented in Equation (3, while the output equation is represented in Equation (4. These two equations alone can represent a linear model, with the help of adding another stage to the equation, it can create a nonlinear model.

$$\mathbf{x}_{\mathbf{1}}^{\mathbf{T}}(\mathrm{k}+1) = [\mathbf{x}^{\mathrm{T}}(\mathrm{k}) \quad \mathbf{u}^{\mathrm{T}}(\mathrm{k}) \quad 1]\begin{bmatrix}\mathbf{A}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{B}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{k}_{\mathrm{x1}}{}^{\mathrm{T}}\end{bmatrix} \tag{3}$$

$$\mathbf{y}_{\mathbf{1}}^{\mathbf{T}}(\mathrm{k}) = [\mathbf{x}^{\mathrm{T}}(\mathrm{k}) \quad \mathbf{u}^{\mathrm{T}}(\mathrm{k}) \quad 1]\begin{bmatrix}\mathbf{C}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{D}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{k}_{\mathrm{y1}}{}^{\mathrm{T}}\end{bmatrix} \tag{4}$$

In this research, the model that will be used in multi-model MPC is by using the second stage of the model. The reason of using two stages of identification relates to create a more accurate model while reducing the complexity of the model while creating a nonlinear model. As for the second stage, the state equation remains the same as Equation (3 but the output equation differs, which is represented in Equation (5. The error ($\mathbf{e_1}$), obtained from the first stage as an error from the actual output and estimated output from the first stage, is then used for the second stage.

$$\mathbf{y}_{\mathbf{2}}^{\mathbf{T}}(\mathrm{k}) = [\mathbf{x}^{\mathrm{T}}(\mathrm{k}) \quad \mathbf{u}^{\mathrm{T}}(\mathrm{k}) \quad \mathbf{e}_1{}^{\mathrm{T}}]\begin{bmatrix}\mathbf{C}_{\mathbf{2}}^{\mathrm{T}}\\ \mathbf{D}_{\mathbf{2}}^{\mathrm{T}}\\ \mathbf{K}_{\mathrm{y2}}{}^{\mathrm{T}}\end{bmatrix} \tag{5}$$

The identification method is done by combining the data what is known and what is not known by transposing the state and output equation. We can denote Equation (3 into grouped matrix form in Equation (6.

$$\boldsymbol{X_1} = \boldsymbol{\Phi_1}\boldsymbol{\theta_1} \tag{6}$$

Using the least square method, it is possible to find the matrix that defines the parameters of the equation, in this case it is $\mathbf{A_1}$, $\mathbf{B_1}$, and $\mathbf{K_{x1}}$ in a grouped form of $\boldsymbol{\theta_1}$. Both $\boldsymbol{X_1}$ and $\boldsymbol{\Phi_1}$ are datas that is known, to find the parameter matrix is just by simply move $\boldsymbol{\Phi_1}$ to the other side of the equation. Because the size of $\boldsymbol{\Phi_1}$ is not square, obtaining the parameter matrix can be obtained with the use of pseudo-inverse which can be represented in Equation (7.

$$\boldsymbol{\theta_1} = \begin{bmatrix}\mathbf{A}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{B}_{\mathbf{1}}^{\mathrm{T}}\\ \mathbf{k}_{\mathrm{x1}}{}^{\mathrm{T}}\end{bmatrix} = \left(\boldsymbol{\Phi_1^T}.\boldsymbol{\Phi_1}\right)^{-\mathbf{1}}\boldsymbol{\Phi_1^T}\boldsymbol{X_1} \tag{7}$$

Repeat the process for the output equation for the first stage and get the matrix of $\mathbf{C_1}$, $\mathbf{D_1}$, and $\mathbf{K_{y1}}$ from Equation (4. After the first stage is complete, using the same method for the second stage to find the parameter matrix, the multi-stage identification is then complete.

2.5 Model Predictive Control Algorithm

Predictive control system is a model-based controller by minimizing a criteria function or sometimes called an objective function. The MPC algorithm has various forms of algorithms, where the only difference is in the process model used to represent the system **(Camacho et al., 2007)**.

Figure 4 shows the basic concept of predictive control system is the use of receding horizon that will predict and optimize the system output several steps ahead. This predictive controller has two types of horizons, namely prediction horizon (Hp) which is the range of output prediction, and control horizon (Hu) which is the range of input prediction to the system. Prediction horizon will be equal or higher than control horizon.

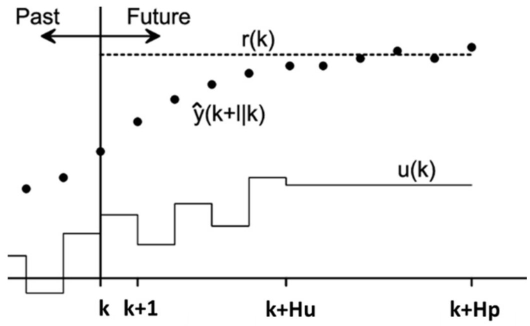


Figure 4. Horizon Concept of Model Predictive Control

Each iteration computes the predicted outputs based on past inputs and outputs, the optimizer then computes the control inputs based on the criteria function of the model so that it follows the reference signal. Errors that occur in the output prediction calculation process can be minimized using the cost function $\boldsymbol{J}$ in a quadratic formula to ensure the minimum solution shown in Equation (8). This cost function is a function consist of three inputs namely the output prediction $(\boldsymbol{y})$ based on the number of prediction horizon, reference $(\boldsymbol{r})$ which also is based on the prediction horizon, and the input difference $(\Delta\boldsymbol{u})$ based on the number of control horizon. Since the reference of the equation is always given, and the controller gives input to the model, so it is necessary to change the output $(\boldsymbol{y})$ into a function of input difference $(\Delta\boldsymbol{u})$. There are also other parameters added to the cost function, the matrix **Q** represent the weight for the error predictions and matrix **R** represent the weight for input difference **(Camacho et al., 2007)**.

$$\boldsymbol{J} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{Hp}} ||\boldsymbol{y}(\boldsymbol{t}+\boldsymbol{k}|\boldsymbol{t}) - \boldsymbol{r}(\boldsymbol{t}+\boldsymbol{k}|\boldsymbol{t})||_{\boldsymbol{Q}}^{\boldsymbol{2}} + \sum_{\boldsymbol{k=0}}^{\boldsymbol{Hu-1}} ||\Delta\boldsymbol{u}(\boldsymbol{t}+\boldsymbol{k}|\boldsymbol{t})||_{\boldsymbol{R}}^{\boldsymbol{2}} \quad (8)$$

Figure 6 shows the block diagram on how the MPC works **(Camacho et al., 2007)**. Each time step the controller needs to calculate the optimization problem above, the output from the MPC will become the future input changes to the system. The past inputs and past output of the system then calculates the predicted outputs based on the model given from the identification. The predicted output then compares to the reference trajectory and creates a future error which then calculates the optimal control input over again with the optimizer by minimizing the cost function. Since this is an optimization problem, input changes and output constraints can also be added, this will allow the MPC controller to become more robust and safer to use for the system.

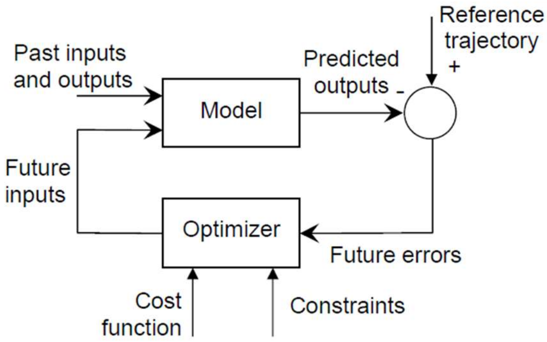


Figure 5. MPC Block Diagram

3. RESULTS AND DISCUSSION

3.1 System Identification

The simulation output data provided is generated by EnergyPlus, while all the environment disturbances includes outside humidity, outside temperature, and solar radiation referes to the weather data of Depok city obtained from meteonorm **(Meteonorm, n.d.)**. The chilled water pump or the actuator is manipulated randomly by N-sample constant method, where it is kept constant between 1-2 time constant to avoid data redundancy **(Wijaya et al., 2022)**. This identification is to see the step response of the system in various temperature constants. Based on previous works, the time hold is kept at 90 time constants for the best results. The system identification parameters is shown in Table 3. Figure 6 shows the random input signal for the fraction chilled water pump flow, where the highest is at 100%, the random input generated is using the PRBS (Pseudo-Random Binary Sequence). Figure 7 shows the disturbances throughout the identification simulation, these include the outside temperetaure, outside tempereature humidity, diffuse horiziontal radiation, and direct normal radiation.

Table 3. System Identification Parmaters

Parameter	Value
Simulation Time	6 days
Time Step	60 seconds
Estimation Data	80%
Validation Data	20%
Hold time	90 time step

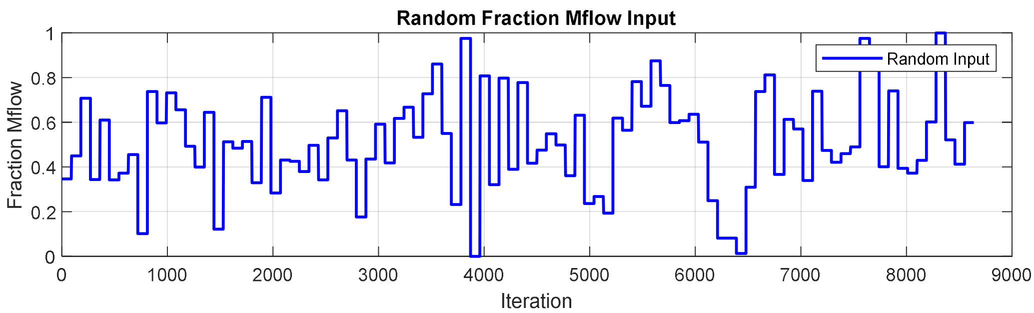


Figure 6. Random Input Signal for Identification Simulation for Chilled Water Pump

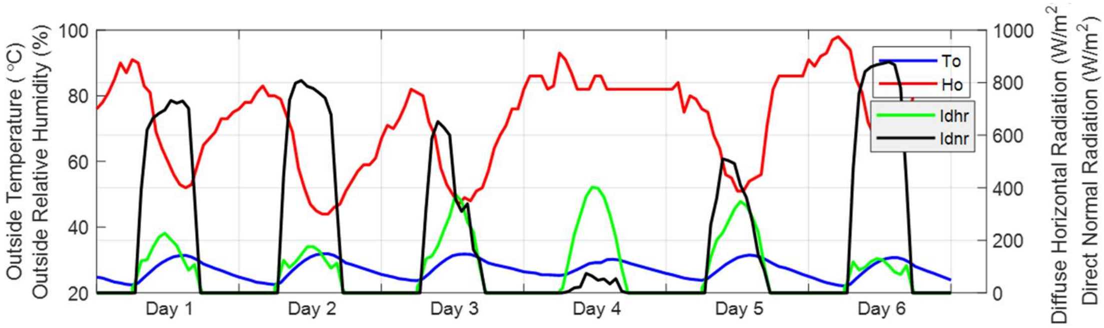


Figure 7. Outside Disturbances for Identification Simulation for MAC Auditorium

Table 4. Parameter Symbols

Symbol	Parameter	Unit
$\dot{m}_{flow}$	Chilled Water Mass Flowrate	(kg/s)
T_r	Room Temperature	(ºC)
H_r	Room Relative Humidity	(%)
T_o	Outside Temperature	(ºC)
H_0	Outside Relative Humidity	(%)
I_{dhr}	Diffuse Horizontal Radiation	(W/m²)
I_{dnr}	Direct Normal Radiation	(W/m²)
C_{pwr}	Average Chiller Power	(Watt)

To find the best set of states to accurately model the building, it is neccessary to use the temperature and relative humidity from both the room and the outside of the building. But this state alone is not enough to represent the system, hence an additional state such as radiations (Diffuse Horizontal Radiation and Direct Normal Radiation) and chiller power is added to represent the HVAC chiller system. Using the FOE for the validation data in Equation (2 will determine the best set of additional state.

Table 5. State Combinations

$\boldsymbol{T_r, H_r, T_o, H_o}$	$\boldsymbol{I_{dhr}}$	$\boldsymbol{I_{dnr}}$	$\boldsymbol{C_{pwr}}$	**FOE**
•				1.92E-01
•	•			1.29
•		•		8.00E-03
•			•	1.19E-05
•	•	•		2.43E-01
•	•		•	1.52E-02
•		•	•	1.22E-02
•	•	•	•	1.74E-02

Based on Table 5, it shows that both the environment radiation does not nessesary make up the building model, this is because the radiation does not directly hit the auditorium, while the chiller power consumption is proportional to the load for the building, this allows the model can take the account for heat load based on the chiller power. In summary, the best possible the combination is by having five states, namely $\boldsymbol{T_r, H_r, T_o, H_o,}$ and $\boldsymbol{C_{pwr}}$.

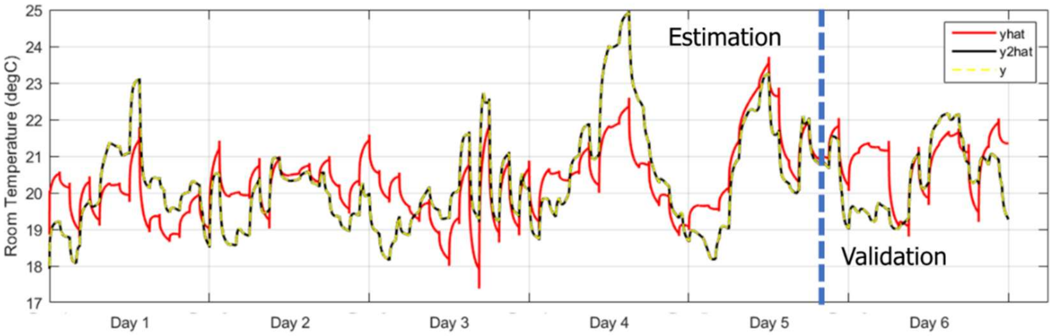


Figure 8. Output Multi-Stage Identfication for MAC Auditorium

Based on Figure 8, three different output data is shown, the actual output from the EnergyPlus simulation in yellow-dashed line, the first layer of output prediction from the first layer of identification model shown in red, and the second layer of identification model shown in blue. The estimation data is used to estimate the model parameters, while the validation data is used to calculate the FOE to ensure that the model can represent the system accurately. The first layer of identification is not able to replicate the output accurately with a total of FOE of 0.9136 which is far from 10%, this means the model cannot be represented in a linear model, meaning the system is nonlinear. In addition, by having another stage of the identification it can accurately represent the actual system with a total FOE of 1.19 x 10^{-5}. Both the number of ranks in controllability and observability matrix is equal to the number of states, this means the system is both controllable and observable.

3.2 MPC Control and Comparison

The schematic of the controller can be seen in Figure 9. The MPC controller will calulate the input signal based on the current and past for both state and output. Since MPC controller has the ability to add constraints for both input and outputs, it can ensure the output and input to be more gentle. Table 6 shows the parameter for MPC controller, based on the objective function on Equation (8, the Q matrix has to be positive definite and the R matrix has to be positive semidefinite. For practical purposes both R and Q matrix use scalar matrix.

Table 6. MPC Controller Parameters

MPC Parameters	Value
Control Horizon (m)	2
Prediction Horizon (p)	4
R matrix	1*$\mathbf{I}$
Q matrix	20*$\mathbf{I}$
$\Delta u_{max}, \Delta u_{min}$	0.1
u_{max}	1
u_{min}	0
y_{max}	27
y_{min}	18

The simulation takes place in one day from 12:00 to 22:00 differs from the identification environments, the reason of taking place in this specific time of day is to simulate the actual usecase of the auditorium, starting from noon to late night. As for the comparison for the proposed controller, an existing On/Off controller is also added. This controller is already built in the EnergyPlus software. The purpose of comparing the two controller is to analyze the difference between the output, control input, and power consumption. Not only for controlling the temperature, but we also need to analyze the indoor thermal comfort standard according to ASHRAE-55 based on Table 7 **(ASHRAE, 2010)**.

Table 7. ASHRAE-55 Indoor Thermal Comfort Standard

Comfort Category	Temperature Range (°C)	Humidity Range (%)
1.0 clo zone	20.0 - 25.0	0 - 80
0.5 clo zone	25.0 – 28.0	0 - 62

We can use the room temperature reference between 20 – 28 °C to simulate a comfortable scenario, a step reference will gradually change for the course of the simulation every two hours to see the response, starting from 23, 22, 21, 24, and 25°C consecutively.

Figure 9 shows the schematic for simulation, the chilled water pump is controlled using the VSD (Variable Speed Drive) by a multi-model MPC controller reading the sensors needed for the controller based on the states from Table 5. The chiller consists of four main parts, the condensor which exchanges gas into liquid, the expansion valve which reduces the pressure and temperature, the evaporator which transfer heat from the chiller loop to the water medium for the coil, and the compressor which increase the pressure by decreseing its volume. The heat transfers from the chiller to the air handling unit through the cooling water coil controlled by the pump. The air handling unit then supplies air from the outside air passing through the cooling coil and returns air from the auditorium through the exhaust air.

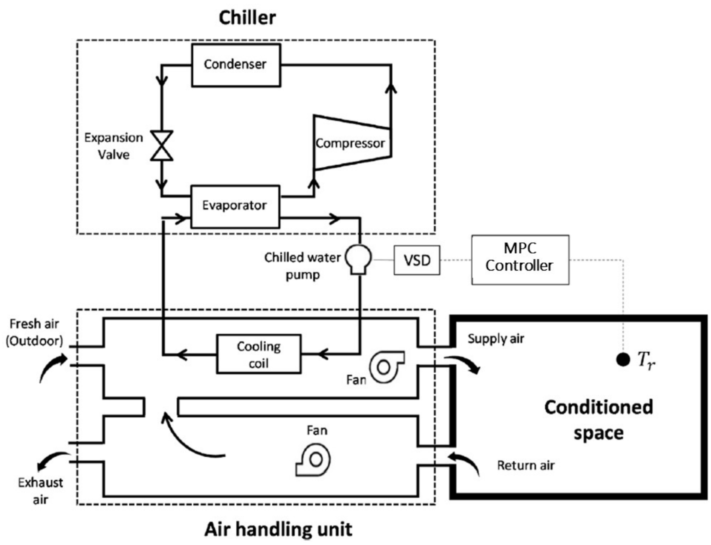


Figure 9. Chilled Water Pump MPC Control Schematic for MAC Auditorium

Figure 10 shows the simulation output, while Figure 11 shows the control signal for both controllers. From the output, we can see that both controllers are able to reach desired output based on the reference given. The initial temperature for the rooom is around 39.5°C, when given the reference of 25°C, both controllers can manage to set the room temperature around in 20 minutes. The control signal for the start of the simulation both shows a maximum signal which tries to ensure that the chiller can set the room temperature to a desired value. When compared, the output for the proposed controller is smoother than the On/Off controller, this is because the signal given to the system is more stable since the proposed controller can give constraints for input changes.

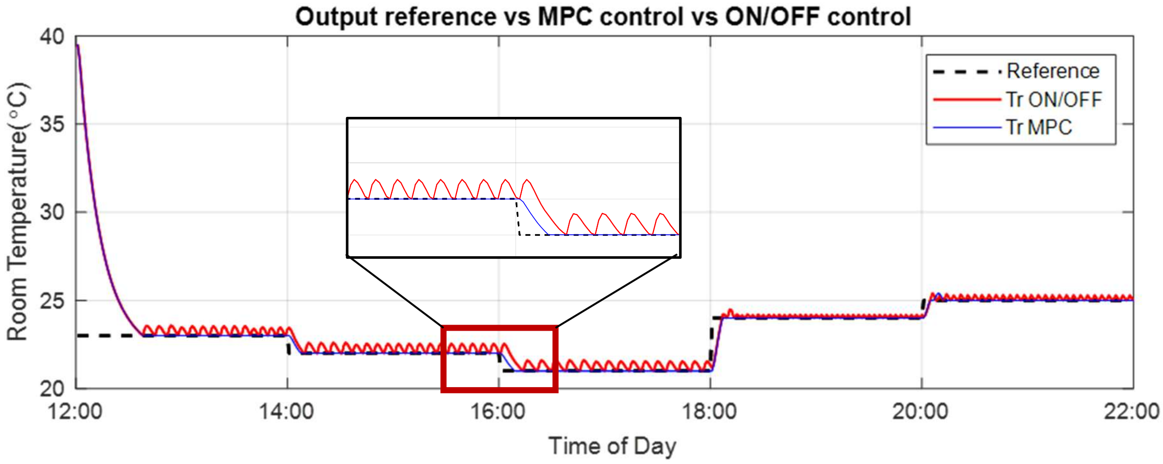


Figure 10. Output Comparison Between MPC Control and ON/OFF Control for Chilled Water Pump for MAC Auditorium

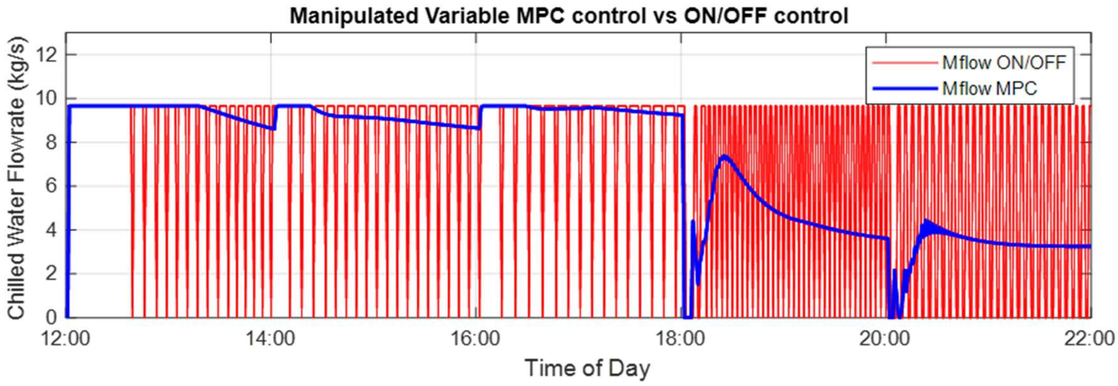


Figure 11. Manipulated Value Comparision Between MPC Control and ON/OFF Control for Chilled Water Pump for MAC Auditorium

We can infer that to lower the temperature, the signal given to the pump is at its maximum. When maintaining to a certain temperature, the proposed controller signal given is stable at a certain level. When compared to the On/Off control, where the only value is only maximum and minimum, this will not only consume more power, but also reduce the lifetime of the pump especially when temperature is set stable in a higher temperature. When changing the temperature to a higher value, the control signal is turned off for the transient response because the outside environment and disturbances will naturally increase the temperature of the room.

Based on Figure 12, we can see the relative humidity for both On/Off and MPC controller, this is to see whether the simulation is able to manage to stay at comfort zone level, which in this case the 1.0 clo zone comfort based on ASHRAE-55 standard shown in Table 7. Where the relative humidity is below 80% in a temperature between 20-25°C. We can see that both controller manages to stay below 80% for the 1.0 clo zone comfort, it can be seen that the initial room relative humidity is low at 30%, this level of relative humidity is caused because initially the auditorium in the simulation is in a closed area with a dry condition with no air circulation in addition to high initial termperature, it then manages to gain relative humidity to 43% at around 12:30 time of day. Both the relative humidity for both controllers jumps by at least 10% after the set point is increased from 21°C to 24°C and maintain the level of relative humidity around 60-70%.

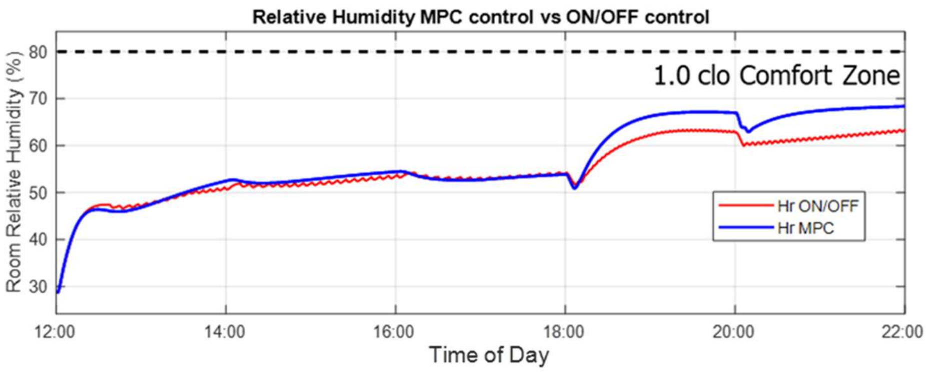


Figure 12. Relative Humidity Comparison Between MPC Control and ON/OFF Control for Chilled Water Pump for MAC Auditorium

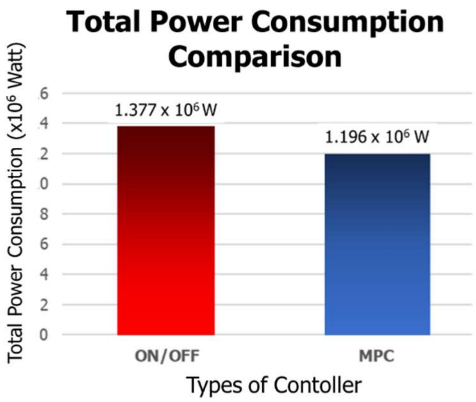


Figure 13. Total Pump Power Consumption Comparison Between MPC Control and ON/OFF Control for Chilled Water Pump for MAC Auditorium

Figure 13 shows the total pump power consumption comparison for the duration of the simulation using the EnergyPlus softwareFigure 13, the total power pump consumption for the on/off controller is 1.377 x 10^6 Watts, while the MPC controller is 1.196 x 10^6 Watts. We can infer that the proposed controller can reduce the total power consumption compared to the existing on/off controller. We can also infer that the pump power has a function that is proporsional to the rotational speed of the pump, which is also proporsional the the flow rate. The higher the rotational speed, the higher energy it requires. This shows that the use of the proposed controller can be an effective operational strategy for chilled water pump to improve building energy efficiency.

4. CONCLUSION

A multi-model MPC controller for optimal chilled water pump for MAC auditorium has been developed using multi-stage plant model identification. The second stage of the identification is able to accurately model the dynamic of the system with a total of FOE of 1.19 x 10^{-5} by having a combination of 5 different states considering of heat loads and environment disturbances. The proposed controller can achieve desired room temperature smoother compared to the existing On/Off controller. The proposed controller performance shows that the response is able to adapt different temperature reference while giving smoother signal input leading to a more robust system by having input and and output contraints. Compared to the existing On/Off control, the proposed controller can reduce the total pump energy consumption approximately by 13.1%. Not only that it can achieve smoother input, more optimal output, and cost effective, but also maintain the level of comfort based on the 1.0 clo comfort zone ASHRAE-55 standard. In conlcusion, the proposed control strategy can be suggested to improve HVAC system for the MAC auditorium for efficient energy consumption.

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