Model predictive control for large-scale cooling tower system using transfer learning model

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ABSTRACT

This study presents a model-predictive control (MPC) for a large-scale cooling water system in an existing factory building. The target system comprises 22 cooling towers (3,000 USRT each), 21 pumps (1,500 m^3/h) and provides cooling water for 22 chillers (2,900 USRT each). The authors selected a federated modeling approach where three different models are combined to describe the dynamic behavior of cooling towers, pumps, and pressure drops in the pipes. Firstly, a physics-based cooling tower model was employed to generate synthetic data under different operational scenarios (e.g. the number of operating fans and towers) which was later used to develop a data-driven model or Artificial neural network (ANN) model. Based on the collected data from the target building, the ANN model was fine-tuned and converted into a transfer learning model where physical knowledge of the cooling towers and actual dynamic behavior extracted from measured data were merged together. The pump and pressure drop models were developed using empirical regression equations. The federated model consisting of the cooling tower, pump and pressure drop models demonstrates a high accuracy in predicting cooling water outlet temperature within a range of 1℃ under time-varying cooling tower fan control. In addition, owing to the MPC, it is found that energy consumption can be saved by 13.4-20.8% over six days in three different seasons (Feb. 21-22, Apr. 21-22, Aug. 20-21).

Introduction

The cooling system in large buildings consists of many different dynamic systems including cooling towers, chillers, pumps, air handling units, fans, etc. Cooling accounts for up to 50-60% of energy use in large buildings and significant energy cooling saving potential exists (Thangavelu et al., 2017). However, it is difficult to apply model-predictive control (MPC) to the cooling system in large buildings because it involves nonlinear interwoven relationship between the different dynamic systems. As an alternative, a rule-based control has been widely used based on facility manager’s experience, engineering intuition and expertise. But it has been well acknowledged that MPC is more advantageous than the rule-based control because it is based on predictive dynamic behavior of system(s) of interest.

Recently, a data-driven modeling approach has been adopted in many MPC studies (Wang et al., 2019; Sala-Cardoso et al., 2020; Ho and Yu, 2021). In addition, reinforcement learning, one of the data-driven approaches, has also been popular because it can be utilized as a simulation model-free approach (Ahn and Park, 2020; Qiu et al., 2020; Fu et al., 2022). The data-driven approach is advantageous in that it does not necessarily require any in-depth expertise and physical knowledge compared to the physics-based approach. However, it demands sufficient quality data and lacks extrapolation ability beyond the training data (Kim et al., 2016; Bourdeau et al., 2019). In many real-life cases, it is difficult to collect enough data under different weather conditions by arbitrarily changing control scenarios, e.g. turning on/off fans, pumps, etc. In contrast, the physics-based model is based on the first-principles of mass and heat transfer theories and straightforward. However, it requires the calibration process to approximate the predictions to reality due to uncertainty of model, resulting in computational burden of individual or whole system depending on the complexity of model.

In this regard, the hybrid model combining physics-based and data-driven approaches has attracted attention. Park et al. (2019) proposed a hybrid chiller model using artificial neural network (ANN) and physics-based models, demonstrating its superior prediction performance. Specially, transfer learning (TL) can be beneficially utilized for developing the hybrid modeling approach because it can easily embed existing knowledge in the simulation model, while keeping the advantages of the data-driven approach (Liu et al., 2021; Zu et al., 2021; Fan et al., 2022).

With this in mind, the authors applied the TL approach for developing the federated cooling tower model encompassing 22 cooling towers (3,000 USRT each) and 21 pumps (1,500 m^3/h) serving 22 chillers (2,900 USRT each). Please note that each cooling tower has one fan at two speeds (high/low, maximum airflow rate of 287m^3/s). Firstly, the cooling tower model was developed using TL. The physics-based cooling tower model was employed to generate synthetic data that were then used to develop a surrogate model, or ANN model. The ANN model was later fine-tuned and converted into a TL model. Also, note that the pump and pressure drop models were developed using empirical equations. In the following sections, we will explain how the federated model was developed and its prediction accuracy followed by an example of MPC for a real-life case.

Target cooling tower system

The target cooling system is located in a large factory building, in South Korea. As shown in Figures 1-2, In the target cooling system, there are a total of 22 cooling towers divide into six cooling tower groups (CTG), with each CTG comprising three or four cooling towers. Each CTG is equipped with a single cooling water pond (Figure 1) where the cooling water from each cooling tower is collected and then transferred to the cooling water pumps (Figure 2). Also, note that the cooling towers are equipped with indirect cooling coils to prevent white plume caused by the water vapor in winter. A total of 21 cooling water pumps comprises two subgroups (CWPG), each supplying cooling water for two different chiller groups (Figure 2). The facility management team regulates cooling water flow rate of each cooling tower by adjusting the valve opening ratio of the main pipe. Also, as mentioned earlier, the cooling tower fan can be controlled by three modes: high, low, and off.

As illustrated in Figure 1, after the cooling water passes through the cooling water pond, it flows into the cooling water header and then is distributed by the cooling water pumps. Note that the cooling water volumetric flow rate and fan speed control are measured in the outlet of each cooling tower. In addition, inflowing and leaving cooling water temperatures are measured as indicated in Figure 2. Also, the outdoor air dry-bulb and wet-bulb temperatures were recorded. The aforementioned data were collected at the interval of one hour from June 2021 to Mar 2023.

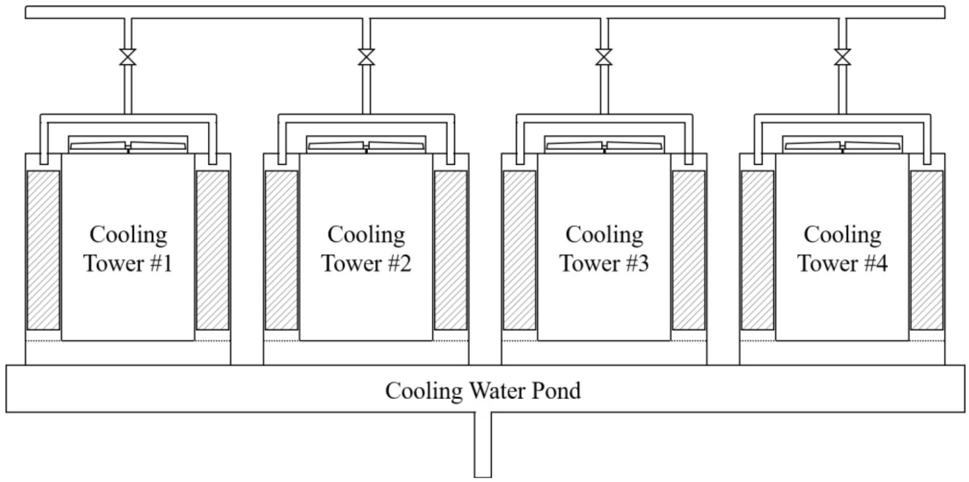


Figure 1. Cooling tower groups consisting of four cooling towers.

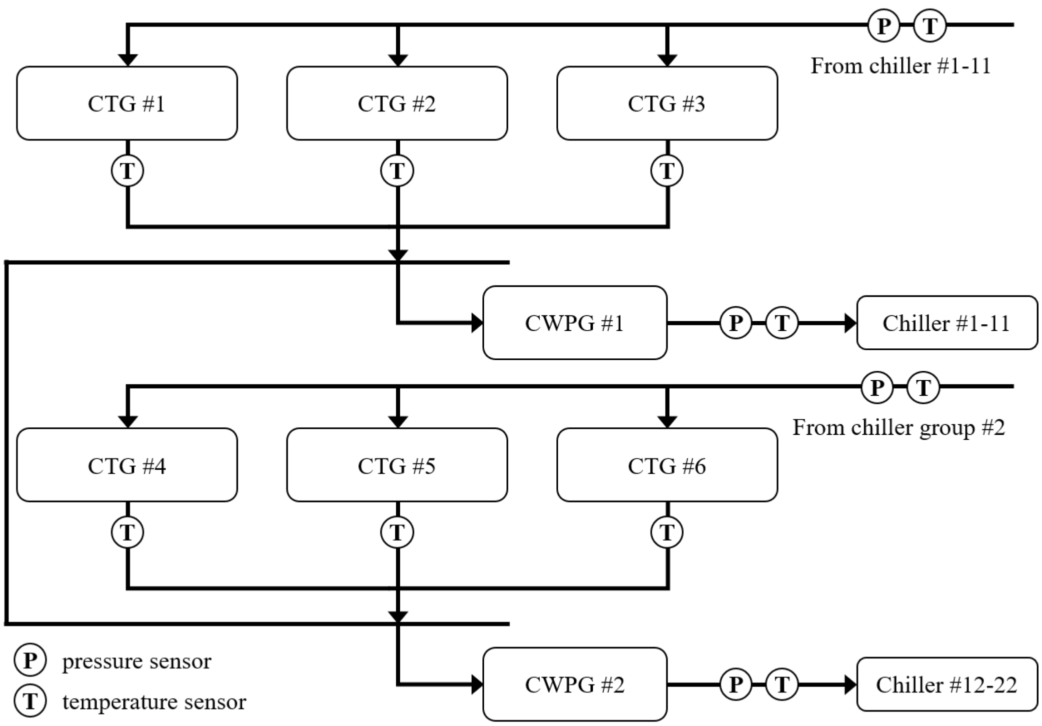


Figure 2. Target cooling water system (CTG: cooling tower group, CWPG: cooling water pump group).

Methodology

Cooling tower model by transfer learning

In principle, the cooling towers remove heat from the chillers by utilizing outdoor air and therefore, it is important to calculate heat transfer between outdoor air and cooling water. Merkel (1925) developed the simplified heat transfer calculation that leverages the difference in enthalpy between saturated air at cooling water temperature and outdoor air. This model is practical but tends to oversimplify the evaporation phenomena of cooling water. Subsequently, many other studies have been conducted to improve the heat transfer model by Merkel (Shryock and Baker, 1961; Osterle, 1991). Jaber and Webb (1989) proposed the ε-NTU based calculation method modified for the cooling tower. Poppe and Rögener (1991) also proposed a mathematical model that calculates the heat transfer based on the saturation state of air through an iterative numerical process. However, the Poppe and Rögener model (1991) demands the time-consuming iterative process until the convergence criteria are met (Kloppers and Kröger, 2004; Klimanek, 2013).

Hawlader and Liu (2002) and Al-Waked and Behnia (2006) used CFD for the heat transfer analysis around the cooling towers. Such CFD approaches can analyze detailed heat and mass transfer phenomena around and inside the cooling towers, but they usually require high computational cost and are not suitable for real-time MPC. As an alternative, empirical equations or data-driven models have been studied. U.S. DOE (2023) proposed two models: regression models with a number of coefficients and CoolTools, counter-flow cooling tower models (Benton et al., 2022). Artificial Neural Network (ANN) models have demonstrated good predictions regarding heat rejection, water outlet temperature, and leaving air condition (Hosoz et al., 2007; Gao et al., 2009).

As mentioned earlier, this study proposes a new approach for the cooling tower model using TL in order to make the best use of physics-based and data-driven models. As illustrated in Figure 3, the target model can be developed by fine-tuning the source model with measured data. In contrast, the source model can be developed using synthetic data generated from physics-based models. Therefore, the target model can achieve high accuracy while keeping extracted knowledge from the source model. In other words, the TL model can overcome two major hurdles of the data-driven modeling approach including *data availability* and *extrapolation ability beyond the training data*.

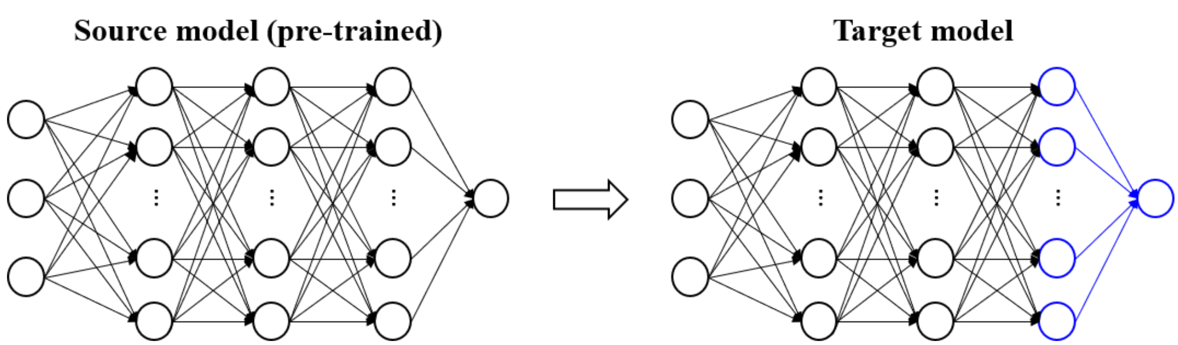


Figure 3. Target cooling tower model by transfer learning (blue circles mean the fine-tuned layer and the model output).

For the target model development, we took three steps: employing a physics-based cooling tower model, generating a surrogate model or *source model*, and fine-tuning the source model with measured data resulting in the *target model*.

As indicated in Figure 1, the cooling water from each cooling tower flows into a single pond. Thus, we lumped three or four cooling towers into one, which can be regarded as a sound engineering assumption, which will be substantiated by comparing the model prediction with measured data in the following section. We used an existing physics-based cooling tower model presented in MathWorks (The MathWorks Inc., 2023). The model is based on the ε-NTU method to calculate the heat removal rate as shown in Equations 1-2. The cooling tower's efficiency (ε)

is calculated by the heat capacity rates (CR) for the air (C_{air}) and cooling water (C_{water}) (Equations 3-4). The overall heat transfer coefficient of cooling tower ($U_{air}A$) is calculated by the mass flow rate of air ($\dot{m}_{air}$), dynamic viscosity (μ_{air}), the Prandtl number of air (Pr_{air}), thermal conductivity of air (k_{air}), the Nusselt number for a circular pipe ($Nu_{laminar\ flow}$), a geometry scale factor for the cooling tower fill material, and other coefficients ($a, b, c,\ \frac{D_{ref}}{S_{ref}}$) (Equation 5). The cooling water outlet temperature is calculated for each cooling tower (Equation 6). The cooling tower pond temperature ($T_{water,pond}$) is calculated as a weighted average of the outlet temperature ($T_{water,outlet,CTG}$) and flow rate ($\dot{m}_{water,CTG}$) of each cooling tower (Equation 7).

$$Q = \varepsilon Q_{max} = \varepsilon C_{min}(h_{water,inlet} - h_{air,inlet}) \text{ (cross-flow)} \tag{1}$$

$$NTU = \frac{U_{air}A}{C_{min}C_{p,air}} \tag{2}$$

$$C_r = \frac{C_{min}}{C_{max}} = \frac{\min\{C_{water}, C_{air}\}}{\max\{C_{water}, C_{air}\}} \tag{3}$$

$$\varepsilon = \frac{1 - e^{-C_r(1-e^{-NTU})}}{C_r} \text{ (cross-flow)} \tag{4}$$

$$U_{air}A = max\left\{((\frac{\dot{m}_{air}}{\mu_{air}})^b \cdot Pr_{air}{}^c \cdot k_{air}\left(\frac{D_{ref}}{S_{ref}}\right)^b \cdot a,\ Nu_{laminar\ flow} \cdot k_{air}\right\} \cdot G_{fill} \tag{5}$$

$$T_{water,outlet} = T_{water,intlet} - \frac{Q}{\dot{m}_{water} \cdot c_{p,water}} \tag{6}$$

$$T_{water,pond} = \frac{\sum(\dot{m}_{water,CTG} \times T_{water,outlet,CTG})}{\sum \dot{m}_{water,CTG}} \tag{7}$$

The authors sampled the operational data, including cooling water inlet temperature, cooling water flow rate, outdoor air dry-bulb temperature, and outdoor wet-bulb temperature, at three-hour intervals. We randomly generated 27 fan control scenarios for each data point and calculated heat removal of cooling towers based on Equations (1-7), resulting in generation of synthetic 150,000 datasets. Please note that the operational conditions were selected with the measured data at the sampling time of one hour from June 2021 to Mar 2023.

Using the 150,000 datasets, the source model or ANN model was developed. The ANN model comprises three hidden layers with 10, 10, and 10 nodes, respectively. Table 1 shows the input and output variables for the ANN model. As the final step, the source model was fine-tuned by retraining the 3rd layer of the ANN model with the measured data and freezing the 1st and 2nd layers. The measured data were collected from the target system for 30 months at interval of one hour. After fine-tuning the ANN model, the *target model* was validated with 2,000 test sets in terms of the mean absolute error (MAE), R^2, and normalized root mean squared (NRMSE).

Table 1. ANN input and output variables

Input variables	Output variable
Cooling water volumetric flow rate of each cooling tower [m^3/h] Cooling water inlet temperature [℃] Outdoor air dry-bulb temperature [℃] Outdoor air wet-bulb temperature [℃] Fan control of each cooling tower [-] Coil valve opening ratio [%]	Heat removal [kW]

Pump and pressure drop models

Each of the pumps (Figure 2) is equipped with an inverter to regulate the cooling water flow rate by varying the motor speed, while maintaining the pipe pressure at an appropriate level. In this study, the pump model was developed based on the manufacturer's catalog data that specifies the pump head, pump efficiency, and motor efficiency as shown in Equations (8)-(10). Subsequently, the shaft power and pump power were calculated (Equations 11-12).

$$Pump\ head = a1 \cdot Q^3 + a2 \cdot Q^2 + a3 \cdot Q + a4 \tag{8}$$

$$Pump\ efficiency = b1 \cdot Q^3 + b2 \cdot Q^2 + b3 \cdot Q + b4 \tag{9}$$

$$Motor\ efficiency = c1 \cdot Q^3 + c2 \cdot Q^2 + c3 \cdot Q + c4 \tag{10}$$

$$Shaft\ power = \frac{Pump\ head \cdot water\ flow\ rate}{Pump\ efficiency} \tag{11}$$

$$Pump\ power = \frac{Shaft\ power}{Motor\ efficiency} \tag{12}$$

where Q is the cooling water flow rate (m^3/h). To account for the pump's operational characteristics according to the inverter, the affinity law was used (Takacs, 2017) as shown in Equation 13 where Q, pump head (H), and shaft power (P) are proportional to the inverter speed ratio (f). In addition, when multiple pumps are operated simultaneously, it is assumed that the total flow rate in the main pipe is equally distributed to each pump.

$$Q_2 = Q_1\left(\frac{f_2}{f_1}\right), \qquad H_2 = H_1\left(\frac{f_2}{f_1}\right)^2, \qquad P_2 = P_1\left(\frac{f_2}{f_1}\right)^3 \tag{13}$$

The pressure drop arises from friction between the cooling water and the pipe surface, bends in the cooling water flow direction, any blockages inside the pipe, etc. Rather than using an analytical model, we took a practical approach to determine the relationship between pressure drop, cooling water flow rate and the number of operating pumps as illustrated in Figure 4. Based on the measured data, we could estimate the operational uncertainty in the pressure drop (Figure 4).

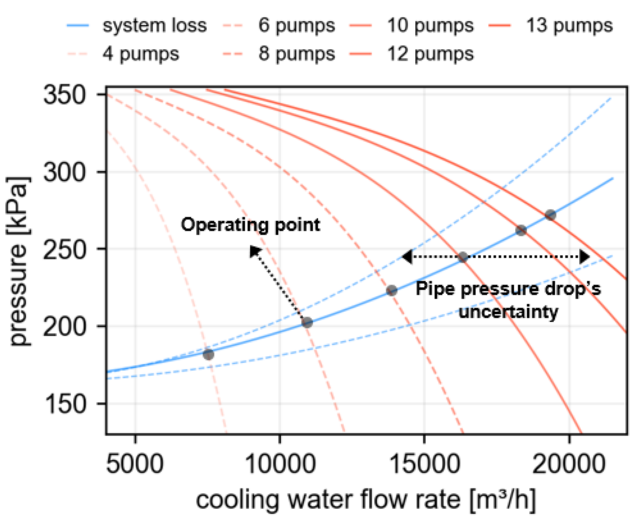


Figure 4. Pressure drop model for pumps #1-13 (For pump number, refer to Figure 2).

Results

Validation of transfer learning model

The authors validated the target model, or TL model using the untrained dataset that was randomly sampled and accounted for 20% of the total dataset. In addition, the authors developed fully data-driven models with the same structure using artificial neural networks (ANN) to assess their performance in comparison with TL models. Figure 5 shows the cooling water temperature at the pond outlet predicted by TL models, with MAE ranging from 0.7℃ to 0.9℃, R^2 ranging from 0.95 to 0.97, and NRMSE ranging from 0.03 to 0.05. In contrast, Figure 6 displays the cooling water temperature at the pond outlet predicted by ANN models. The ANN models exhibit superior predictive performance across all three metrics, with MAE lower than 0.5℃, R^2 higher than 0.98, and NRMSE lower than 0.03.

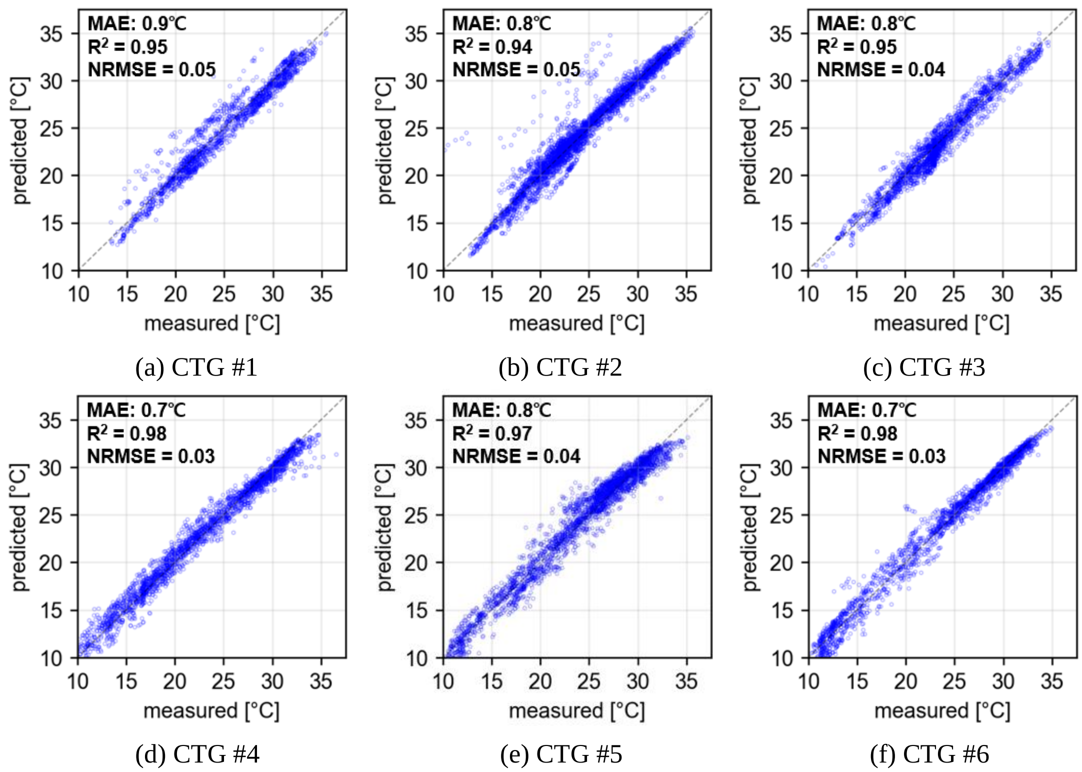
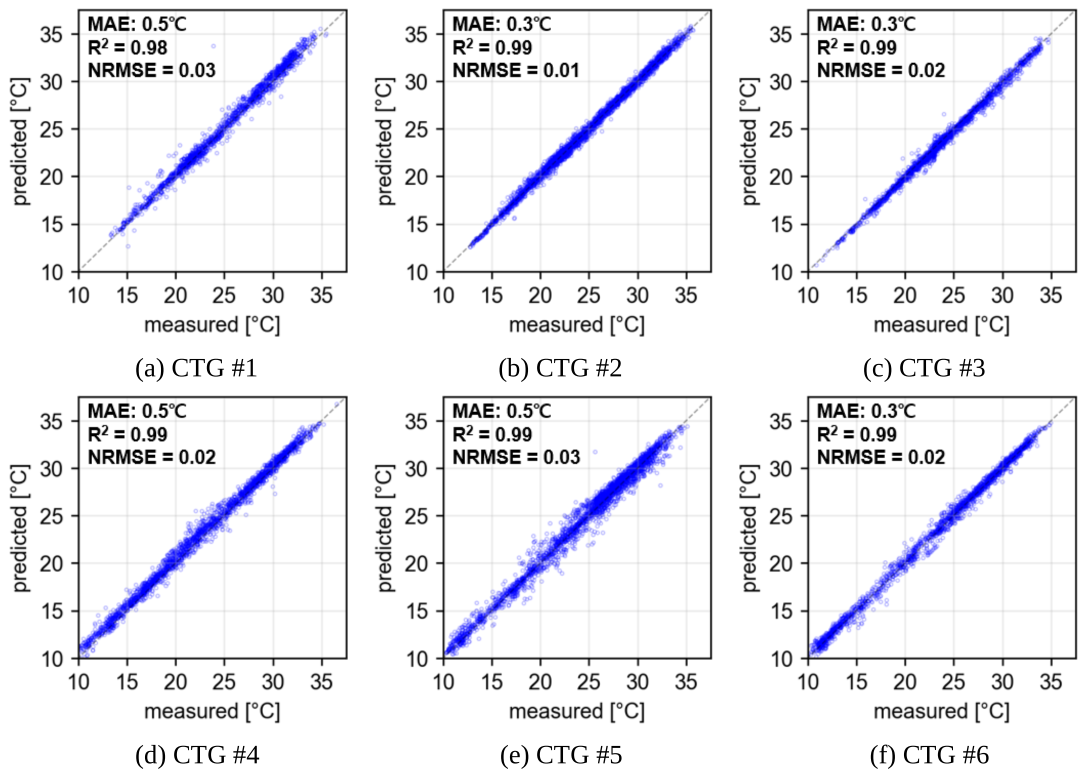


Figure 5. Cooling water temperature prediction by transfer learning model (CTG denotes cooling tower group illustrated in Figures 1-2).



(a) CTG #1 (b) CTG #2 (c) CTG #3

(d) CTG #4 (e) CTG #5 (f) CTG #6

Figure 6. Cooling water temperature prediction by artificial neural network model (CTG denotes cooling tower group illustrated in Figures 1-2).

The authors simulated fan control of one of cooling tower models under the virtual conditions to compare the physical causality between the TL and ANN models (Table 2). Figure 7 demonstrates the results of physical causality. On the x-axis, the fan value represents the aggregate of all four cooling towers, with high fan speed calculated as 2, low fan speed as 1, and stop as 0. It is notable that the lowest outlet temperature occurs when the fan setting is at 6 for ANN. Additionally, when the fan setting is at 7, the calculated outlet temperature is lower than 8. In contrast, the outlet temperature of TL shows a linear relationship with the number of Fan and maintains physical causality. This due to the data imbalance resulting from operations mainly using high fan speed. The fully data-driven models face challenges in accurately capturing the system dynamics when sufficient data is unavailable. As a result, the hybrid models combining physics knowledge and operation data ensure reliable results, even if they are slightly less accurate, making them suitable modeling approaches for MPC.

Table 2. Assumed operational conditions

Input variables	August	March
Cooling water volumetric flow rate of each cooling tower [m^3/h]	1,450	1,100
Cooling water inlet temperature [°C]	35.5	25.1
Outdoor air dry-bulb temperature [°C]	33.5	11.3
Outdoor air wet-bulb temperature [°C]	26.9	10.8

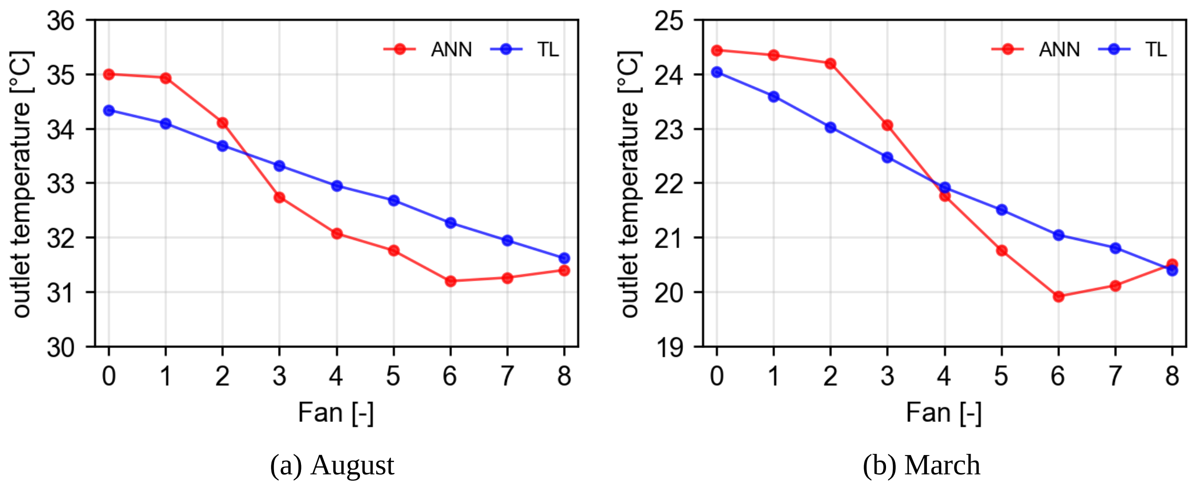
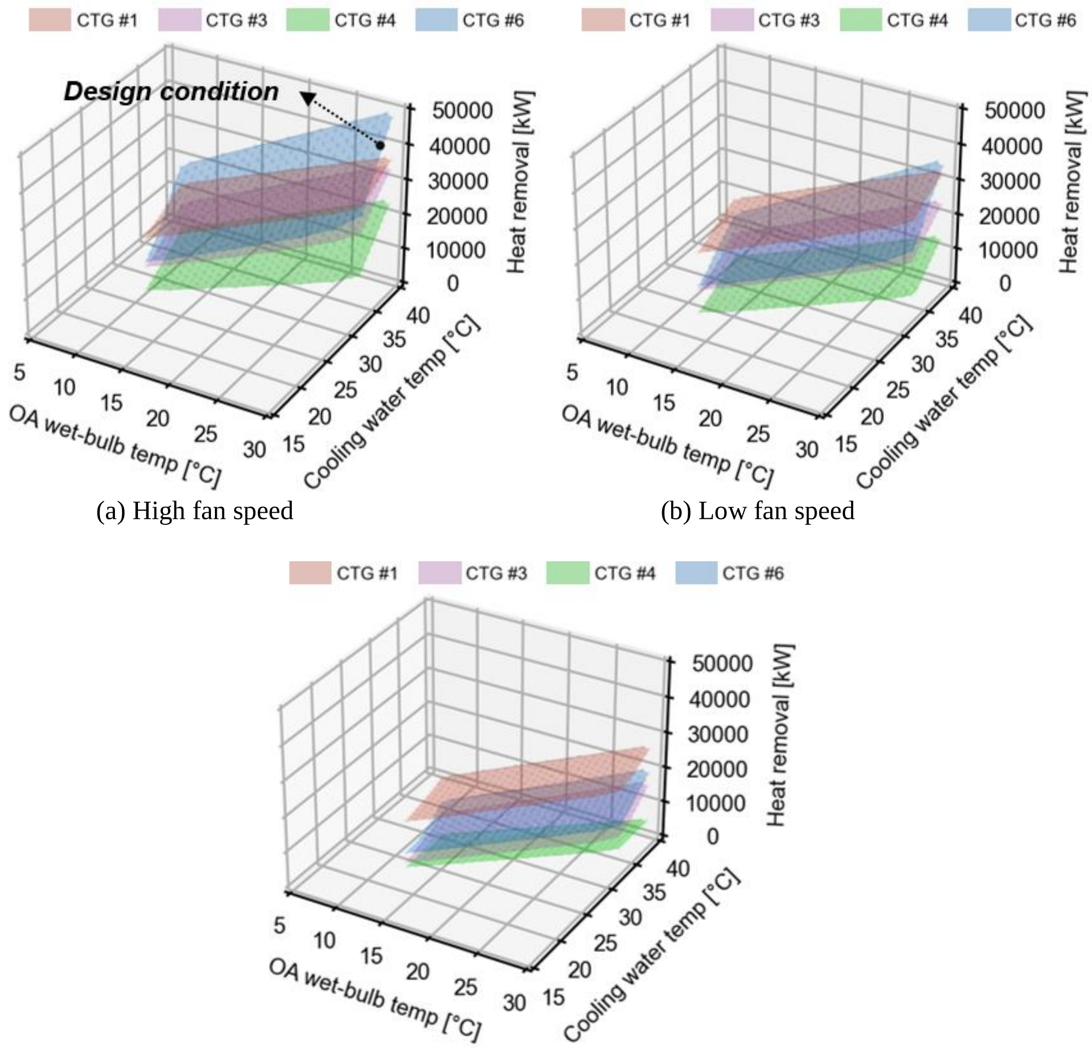


Figure 7. Physical causality comparison

Cross-comparison of CTGs

For MPC, control variables are determined by considering the performance priority of CTGs derived from develop system models. The identification of priority among CTGs obtained from these models can also help us understand the selection of control variables and the systems' performance degradation. In this section, authors conducted a comparative analysis of performance of CTGs under specific conditions. Except CTG #2 and #5, the other four CTGs (#1, #3, #4, #6) have the same number of cooling towers.

Figure 8 illustrates a cross-comparison of the heat removal rate of each cooling tower group. In Figure 8(a), a black dot means the design condition specified in the manufacturer's specification. Except for CTG #6, three cooling tower groups (#1, #3, #4) fall short of meeting the design condition at high fan speed mode. While CTG #6 outperforms the other groups at high fan speed mode, CTG #1 performs best at low fan speed and fan off modes (Figure 8(b)-(c)). Compared to other CTGs, CTG #4 underperforms most regardless of the fan control. This might be attributed to many unknown factors, e.g. fan efficiency, unwanted air recirculation from neighboring cooling towers, blocked cooling tower fills, etc. Conclusively, in order to optimize system performance in MPC, control variables to maximize fans of CTG#6 in MPC can be determined. In addition, the priority identification can also improve system efficiency by informing pre-determined order of high heat removal efficiency to operators. Please note that a fan's nominal power is 130 kW.



(a) High fan speed

(b) Low fan speed

(c) Fan off

Figure 8. Cross-comparison of heat removal rate between cooling tower groups

Optimal control

Based on the simulation, the authors conducted an optimal control study of the target system at the interval of three hours for six days comprising two days each of summer, winter, and mid-seasons. As the target building had a slow dynamic change of cooling load to perform control on one-hour or two-hour intervals, the authors chose three-hour interval for applying a simulation study. The possible control variables, objective function and constraints in the target system are as follows (refer to Figure 2 regarding the cooling tower and pump numbers. Also, note that the lower bounds of the operating fans and pumps are strictly limited by the facility team):

Control Variables

- $0 \leq$ the total number of operating cooling tower fans (CTG#1-#3) ≤ 11
- $0 \leq$ the total number of operating cooling tower fans (CTG#4-#6) ≤ 11
- $4 \leq$ the number of operating cooling water pumps (#1-#13) ≤ 13

- $2 \leq$ the number of operating cooling water pumps (#14-#21) ≤ 8

Objective function

- min $\sum(Power_{cooling\ tower\ fan} + Power_{cooling\ water\ pump})$

Constraints

- $\Delta T_{cw,ope} - 2.5°C \leq \Delta T_{cw} \leq \Delta T_{cw,ope} + 2.5°C$
- $\Delta T_{cw,CTG} \leq \Delta T_{cw} + 3.5°C$ (for each CTG)
- $\frac{\sum(\dot{m}_{water,CTG} \times T_{water,outlet,CTG})}{\sum \dot{m}_{water,CTG}} \leq T_{cooling\ water,inlet} - \Delta T_{cw}$

Figure 9 illustrates the process of MPC in details. Firstly, the heat removal at each time step is calculated using the cooling water volumetric flow rate (Q) and the temperature difference in cooling water (ΔT_{cw}) between the inlet and outlet from operational data. Then, required pressurization from the pump was determined based on the operational data, including the number of pumps and Q, using a pump model. Then, the feasible number of operating pumps was determined to meet ΔT_{cw} and required pressurization. Specifically, the number of pumps was selected as a feasible control variable calculating Q to meet the range within $\pm 2.5°C$ of the operation ΔT_{cw} ($\Delta T_{cw,ope}$).

Subsequently, the cooling water outlet temperature ($T_{cw,out}$) was calculated according to the fan control modes. However, if we explore three speed modes for 22 fans each, the number of possible control options is 3^{22}, greater than ten billion. Hence, instead of the exhaustive search, we selected control variables that calculate ΔT_{cw} within $\pm 3.5°C$ for each CTG as a hierarchical search. As a result, the cooling water outlet temperature was calculated by Equation 7 and the optimal variables were selected which satisfying the ΔT_{cw} and minimizing the system energy consumption. Using the operation data of each timestamp, the federated model calculated only optimal variables without predicting future state of system and outdoor conditions. Then, it calculated the system energy by applying these optimal control variables.

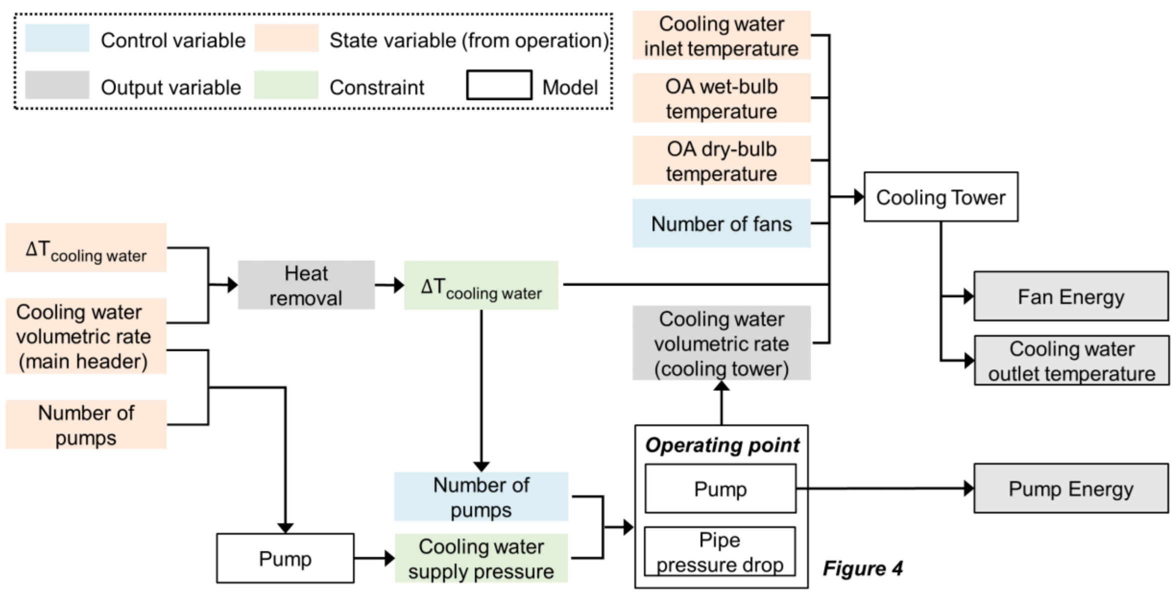
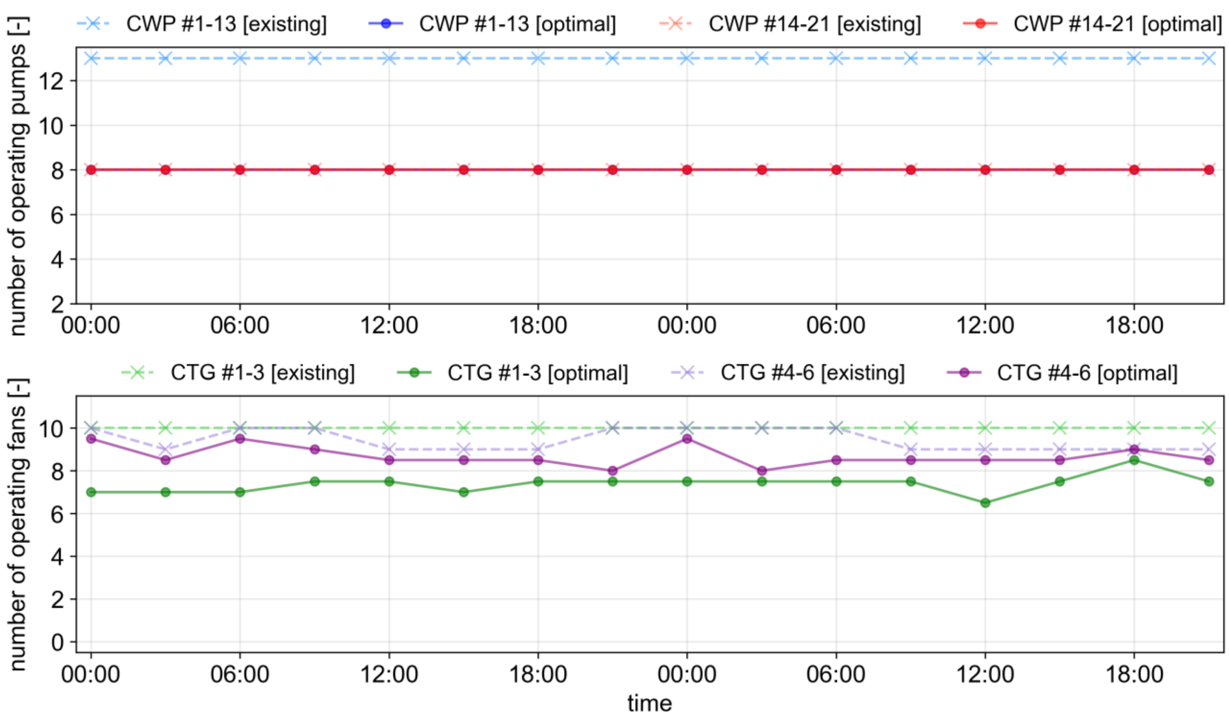


Figure 9. Optimization optimization of the target system.

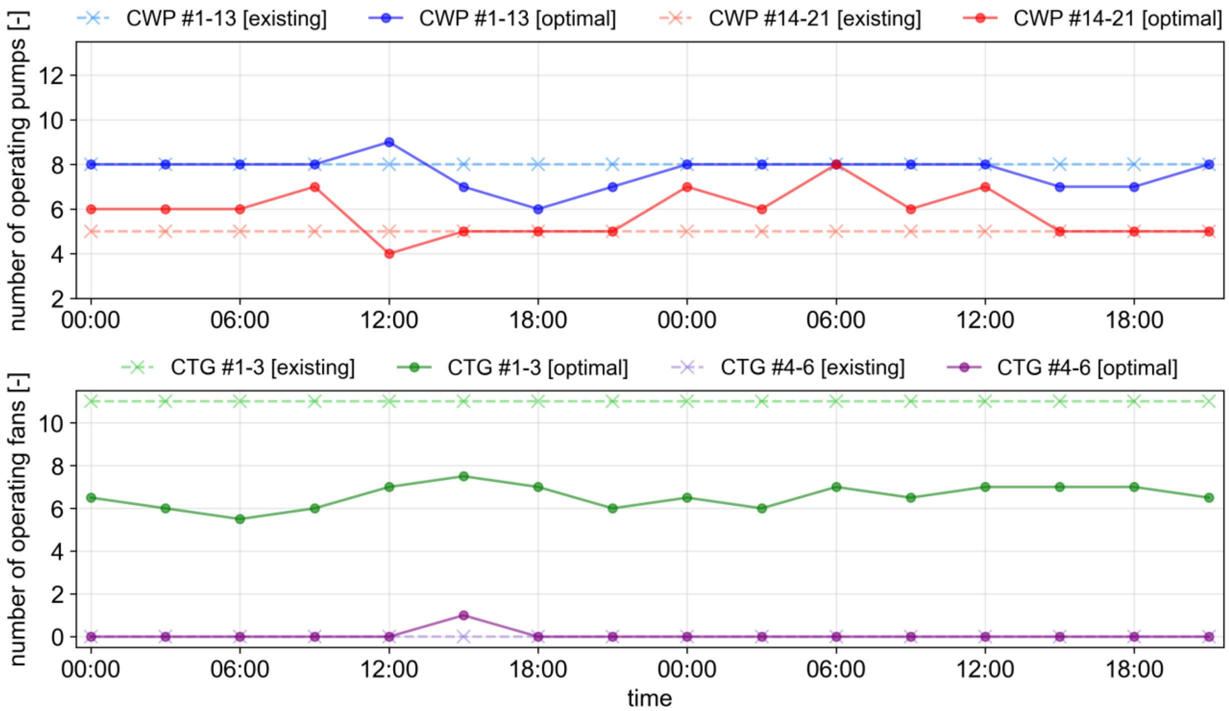
Figure 10 shows the optimal control results. During summer days (August 20-21, Figure 10(a)), the existing control operated 13 CWPs (#1-13) and 8 CWPs (#14-21), while optimal control could reduce the number of operating pumps and fans. In other words, as Q of each cooling tower decreases, ΔT_{cw} increases accordingly and fans of CTG #4-6 were also reduced. As a result, the optimal control could save energy by 20.8% (existing: 257,430 kWh, optimal: 203,925 kWh).

For winter days (February 21-22, Figure 10(b)), the optimal control increased the number of CWP #14-21 and maintained the number of operating fans of CTG #4-6, and also reduced the number of operating fans of CTG #1-3. Due to low outdoor air temperature in February, CTG #4-6 could efficiently remove the heat by increasing Q without increasing the number of operating fans. Consequently, the optimal control could save 13.4% of the total energy (existing: 150,033 kWh, optimal: 129,972 kWh).

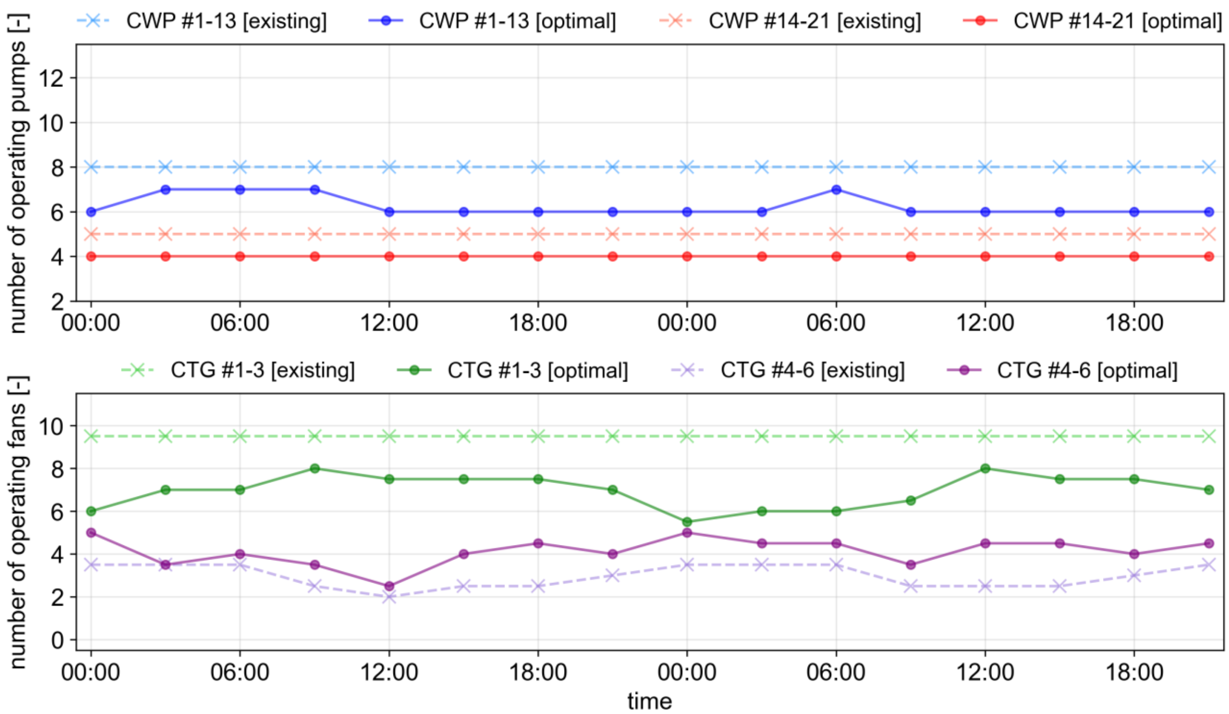
For intermediate days (April 20-21, Figure 10(c)), the optimal control reduced the number of CWPs, similar to winter. Due to comparatively low outdoor air temperature, the optimal control could search the reduced number of cooling tower fans, while handling the required heat removal rate. Accordingly, the optimal control achieved a 14.7% reduction in energy consumption (existing: 151,842 kWh, optimal: 129,549 kWh).



(a) August 20-21



(b) February 21-22



(c) April 20-21

Figure 10. Optimal control results of the target system for three seasons.

Conclusion

The data-driven model has attracted much attention for its good accuracy and low computation demand. However, it has several limitations such as data availability and extrapolation ability beyond the training data. In this regard, the authors developed the transfer learning model approach for a large-scale cooling water system in an existing building. The target system comprises 22 cooling towers (3,000 USRT each), 21 pumps (1,500 m^3/h) and provides cooling water for 22 chillers (2,900 USRT each). To handle such a large-scale target system, the authors selected a federated modeling approach where cooling tower, pump, and pressure drop models are combined.

Firstly, the cooling tower model was developed using transfer learning where the 1st principles of the cooling tower and its actual dynamic characteristics extracted from on-site measured data were beneficially merged together. The pump and pressure drop models were based on empirical regression equations. The federated model demonstrated a good-enough accuracy and physical causality (MAE: 0.7℃ - 0.9℃, R^2: 0.94-0.98, and NRMSE: 0.03-0.05) compared to the data-driven model and then was used for optimal control of the target system. Owing to the MPC, it is found that energy consumption can be saved by 13.4-20.8% over six days in three different seasons (Feb. 21-22, Apr. 20-21, Aug. 20-21).

The proposed modeling methodology using the transfer learning could be widely applied to many MPC applications in existing buildings because it could overcome major hurdles of the data-driven model including *data availability* and *extrapolation ability*.

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