Energy saving quantification/control optimization

Energy saving effect on VAV・VWV・CO2 concentration control

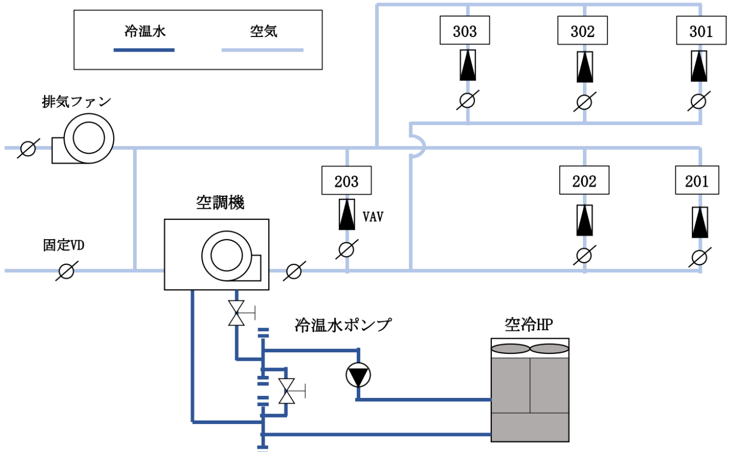


図-2 対象システム概要

- Evaluated energy efficiency and room temperature controllability of each control by combining VAV/CAV control and VWV/CWV controlBy calculating control conditions of fans and dampers in as much detail as possible, changes in room temperature and energy consumption during load changes can be explained.Parameters adjusted for periods of high load resulted in deteriorated controllability at other times of the year, confirming the possibility of improving controllability by readjusting parameters on a monthly basis.

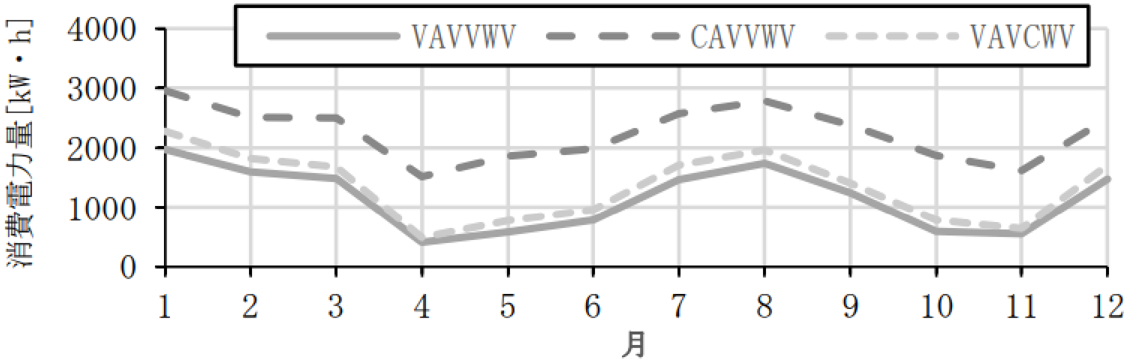


図-10　各月の総消費電力量

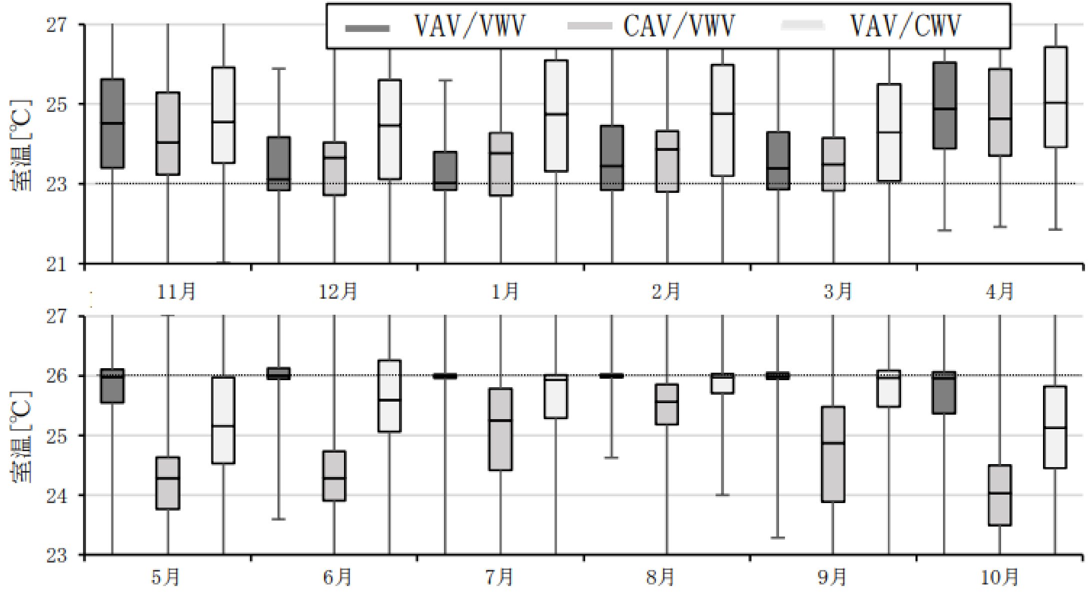
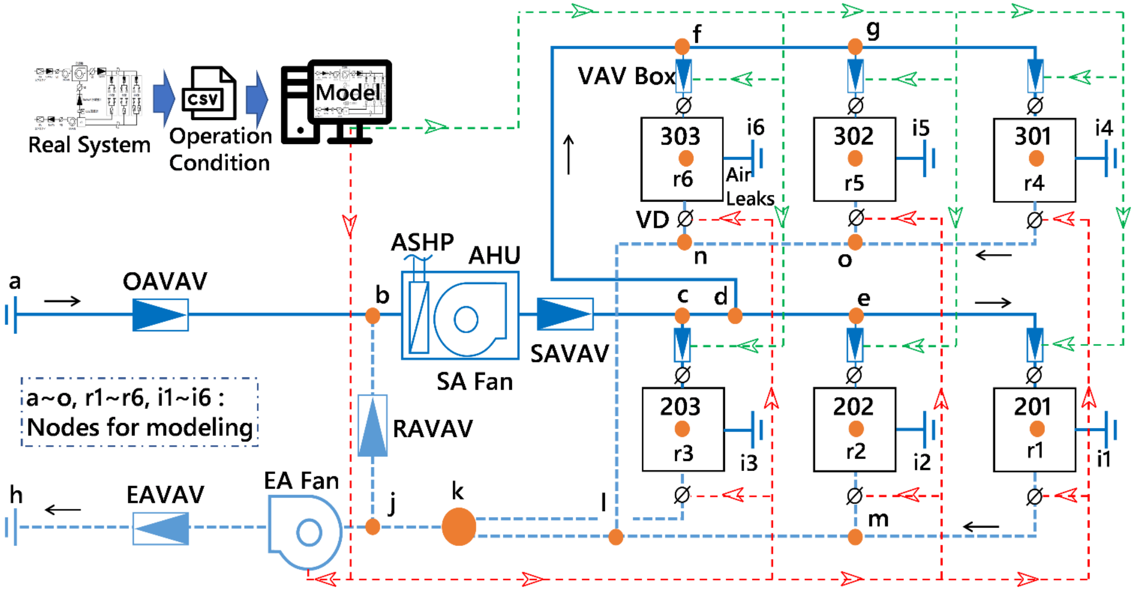


図-11 制御ごとの室温の制御性 上：暖房時　下：冷房時

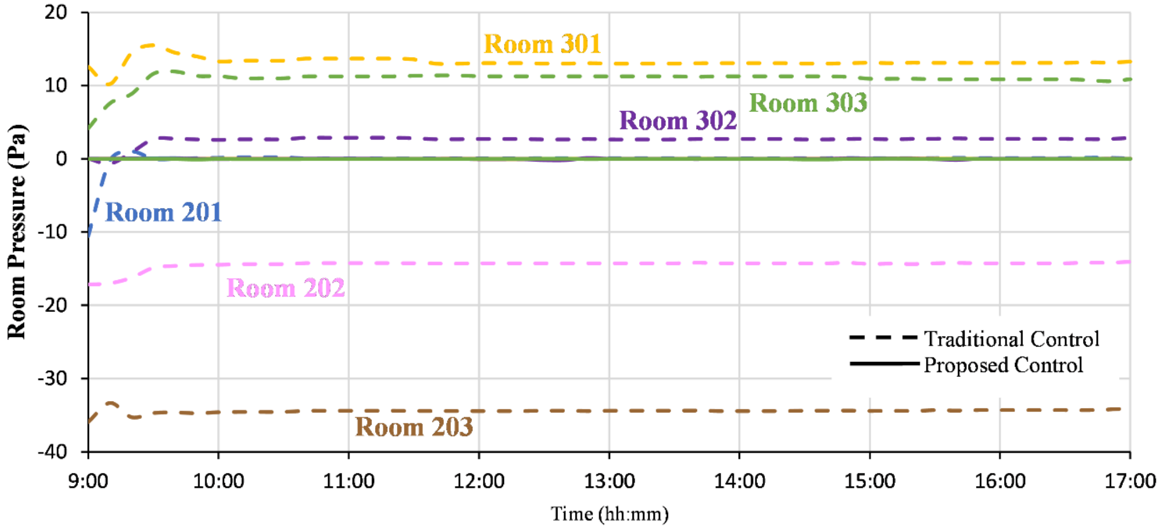
https://doi.org/10.18948/shase.46.293_23

Energy saving quantification/control optimization

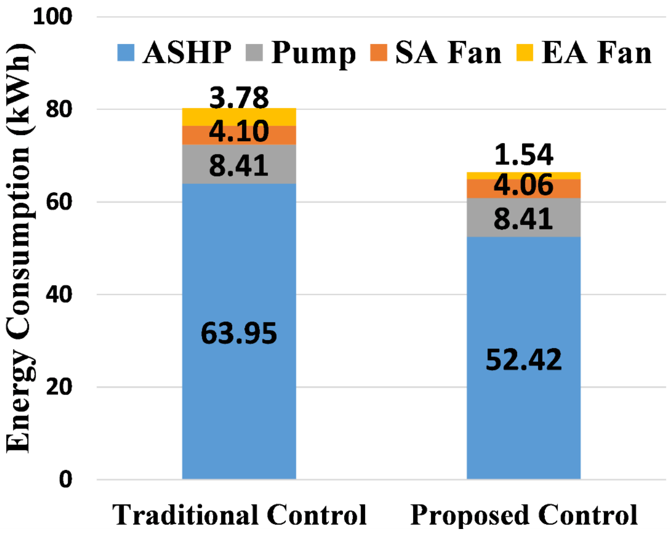
Room pressure neutralization



Conceptual Diagram of Model-Based Control



Full load operation



Partial load operation

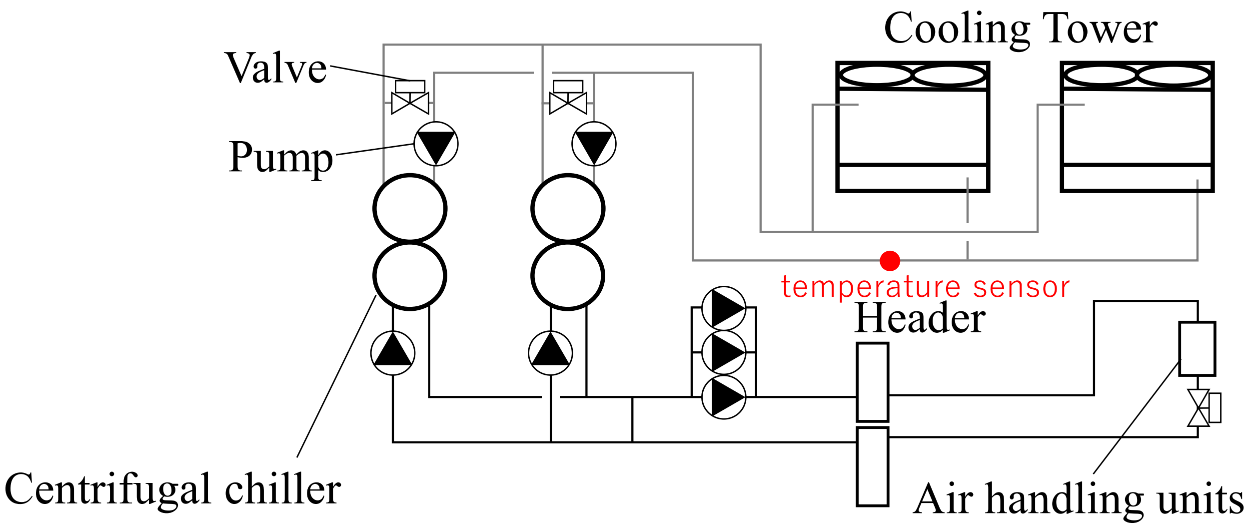
- Validated 6-room VAV system model
  - Simulated airflow, room pressure and energy consumption
  - Demonstrated good agreement with measured data
- Model-based static pressure reset control strategy
  - Capable of neutralizing room pressure and maintaining desired indoor air temperature
  - Evaluated under both full-load and partial-load summer operating conditions

https://publications.ibpsa.org/conference/paper/?id=bs2023_1293

Automated fault detection and diagnosis

Dataset generation

Example: Cooling tower condenser water outlet temperature sensor bias (+2 °C)



- We developed python-based HVAC simulation program, phyvac.
- Phyvac can be used to flexibly build simulations of HVAC systems, incorporating fault conditions as needed.
- As an example, the bias of the cooling tower coolant outlet temperature sensor was modeled as a heat source system failure and the results were analyzed.
  - ➢ The results were also compared to the LBNL FDD data set and validated.

```
# Define sensor error bias
dt_CT_tout = 2.0

# Define classes for cooling tower and cooling tower fan
PID control
CT = pv.CoolingTower(kr=0.1, ua=143000)
PID_CT = pv.PID(kp=0.005, ti=600, kg=-1, a_max=0.498)

# Define calculation formula for cooling tower condenser
water outlet temperature setpoint
def cal_sv_CT_tout(t_wb, sv_min=11.0):
    sv = t_wb + 4
    if sv < sv_min:
        sv = sv_min
    return sv

# Calculate at each time step
For i in range(24*60*365):
    # Calculate the setpoint
    CT_tout_sv = cal_sv_CT_tout(t_wb=t_wb)
    # Control Cooling tower fan speed based on biased
    condenser water temperature
    CT.inv = PID_CT.control(sv=CT_tout_sv,
             mv=CT.tout_w + dt_CT_tout)
```

Modified code

	Chiller	Primary pump	Condenser pump	Cooling tower	Secondary pump	Total
Unfaulted	927	45	127	104	148	1352
Cooling tower bias+2	913	45	127	131	148	1364
Impact ratio	-1.6%	0.0%	0.1%	25.2%	0.0%	0.9%

Yearly power consumption by the fault

https://publications.ibpsa.org/conference/paper/?id=bs2023_1293

Automated fault detection and diagnosis

AFDD using deep learning

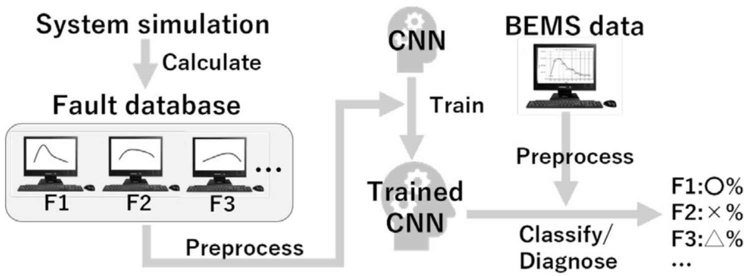


図-1 AFDD 手法概要

図-5 AFDD 画面例

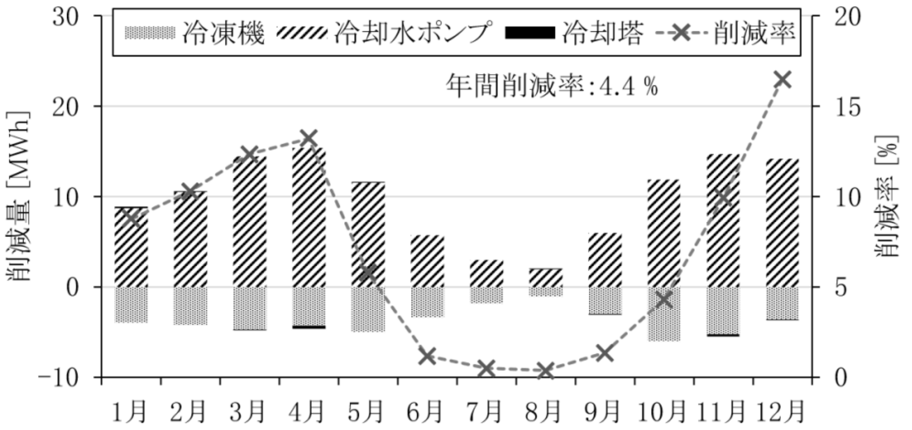


図-10 設定値変更によるシステム消費電力量削減

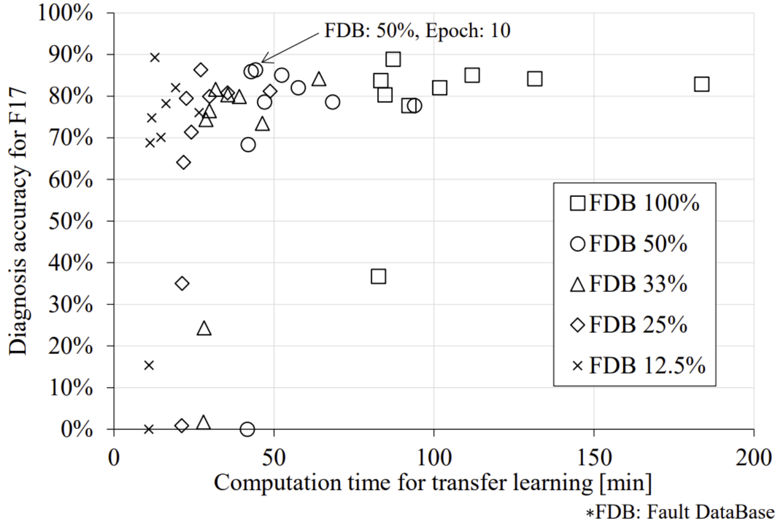


図-20 不具合データベースの量と計算時間・診断精度

- Automatic defect detection and diagnostics by feeding the fault dataset generated by Phyvac to CNN.
- By diagnosing BEMS data with the trained CNN, it is visualized that the characteristics of faults that occur change depending on the season (when load conditions change).
- Effectiveness of correcting faults is also calculated by phyvac.
- Efficient generation of fault datasets through transfer learning was also tackled.

https://doi.org/10.18948/shase.47.306_1, https://doi.org/10.1016/j.enbuild.2023.112877

Demand response

Behavior of power demand and indoor thermal environment

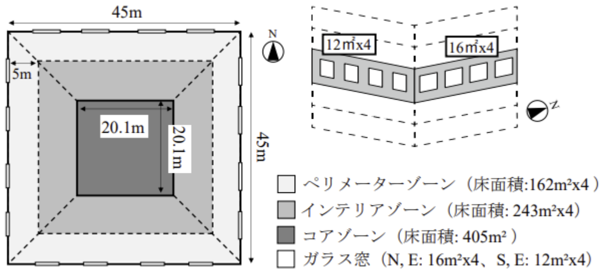
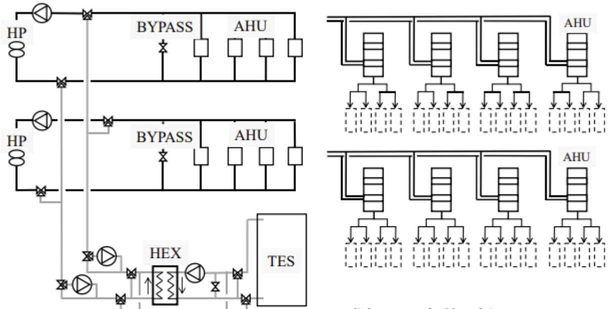


図-1　基準階の平面図と立面図（南東）



(a)　熱源側システム図　　(b)　四方位ごとに 4 つの VAV 末端を有する枝管

注　(b) の上下の系統はペリメーターゾーンとインテリアゾーンに対応する。

図-2　空調システム図

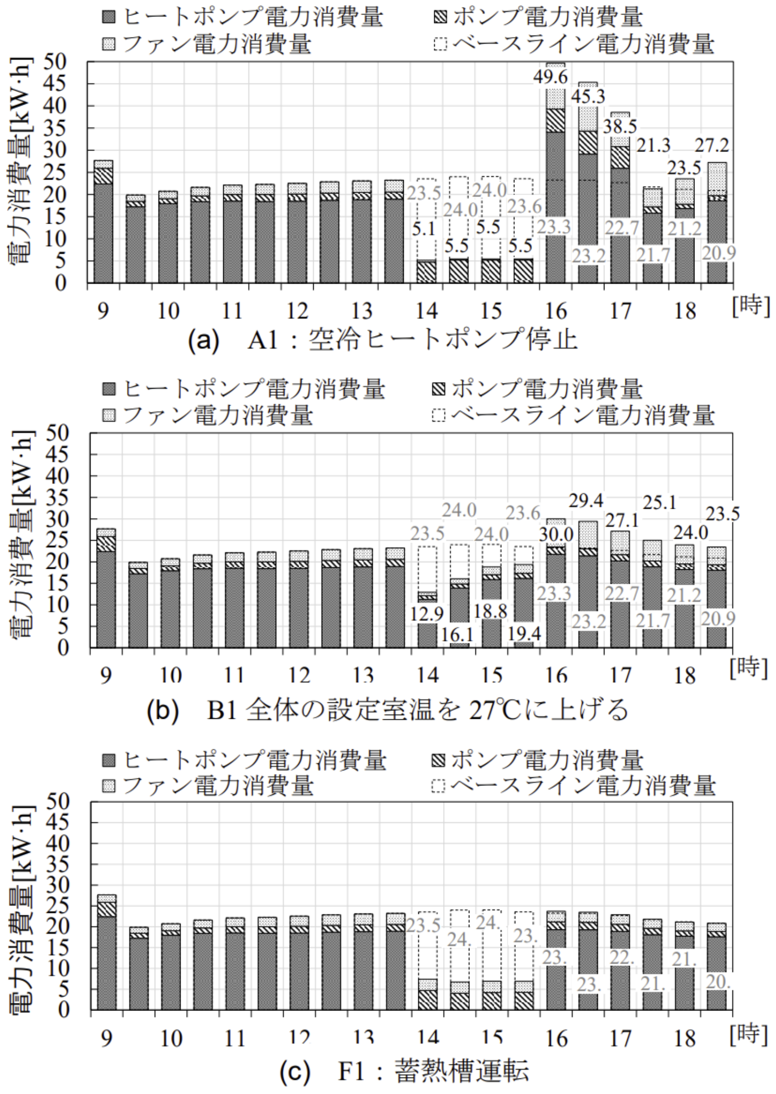


図-7　各 DR ケース電力デマンド（17 日）

- Build simulations of building, water-side and air-side HVAC systems
- Calculate and analyze changes in power demand and room temperature due to DR
  - DR by shutting down heat sources and changing room temperature settings affects control stability and room temperature
  - A rebound in power demand immediately after the end of DR was also confirmed
  - Since total power consumption increases, it is important to consider the trade-off relationship.
  - DR effects vary depending on the thermal load, so load forecasting technology is also important.

https://doi.org/10.18948/shase.46.286_21

Demand response

Low carbon emission control of chiller using model predictive control

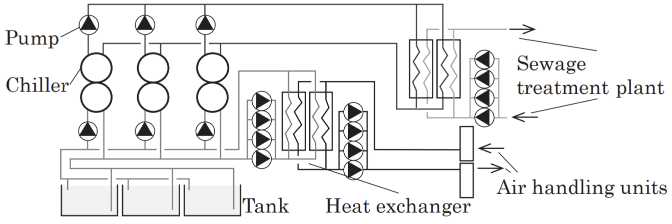


Fig.4 Target system

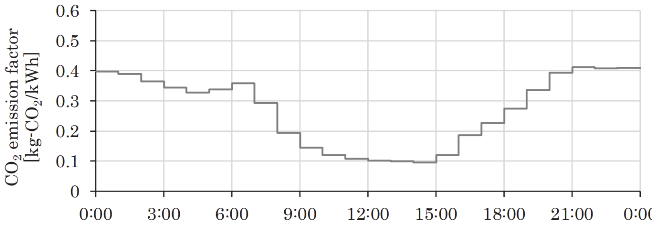


Fig.2 Minimum CO_2 emission factor (May 14th)

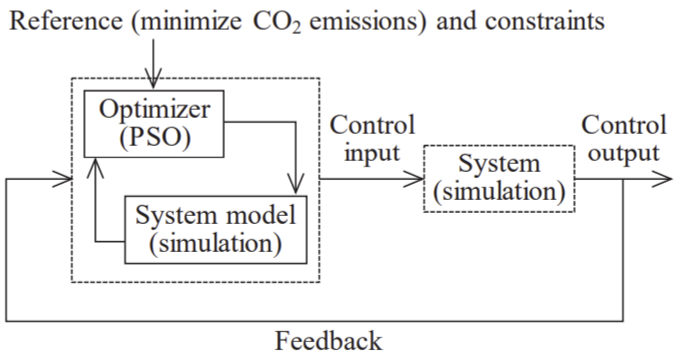
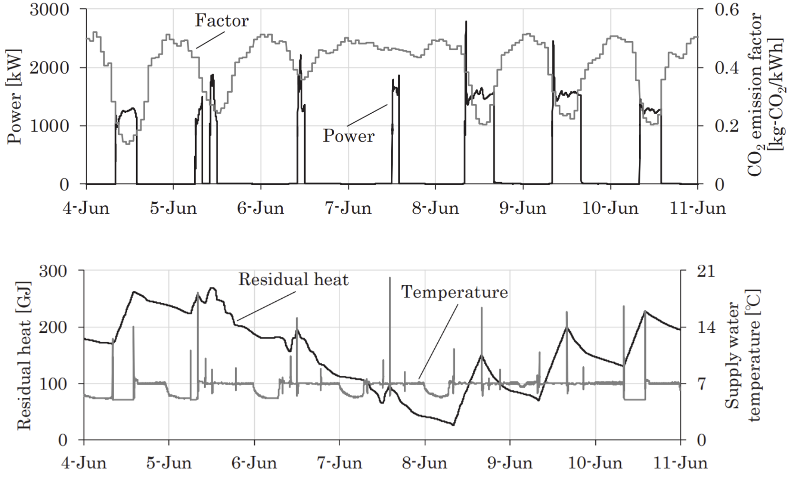


Fig.8 Structure of the calculation

- Build a simulation of a system of a heat source system with a heat storage tank
- Applying model predictive control to optimize the operation of the chiller to minimize CO2 emissions
  - Utilized hourly dynamic CO2 emission coefficients
  - Provide constraints to prevent supply temperature from rising due to insufficient residual heat storage
  - On days with high CO2 emission coefficients, such as rainy days, the system is checked for full heat storage on the previous day
  - When system simulation is used in MPC, it takes time to search for optimal values. Therefore, it is necessary to devise control variables (in this case, only start/stop of the chiller)



System behavior by the MPC

https://doi.org/10.18948/shase.46.286_21