Research objectives

Keywords: Batteries, Thermal energy storage, Heat source machine, Optimal control, Artificial intelligence, Annual optimisation, District heating and cooling, Heat-sharing network

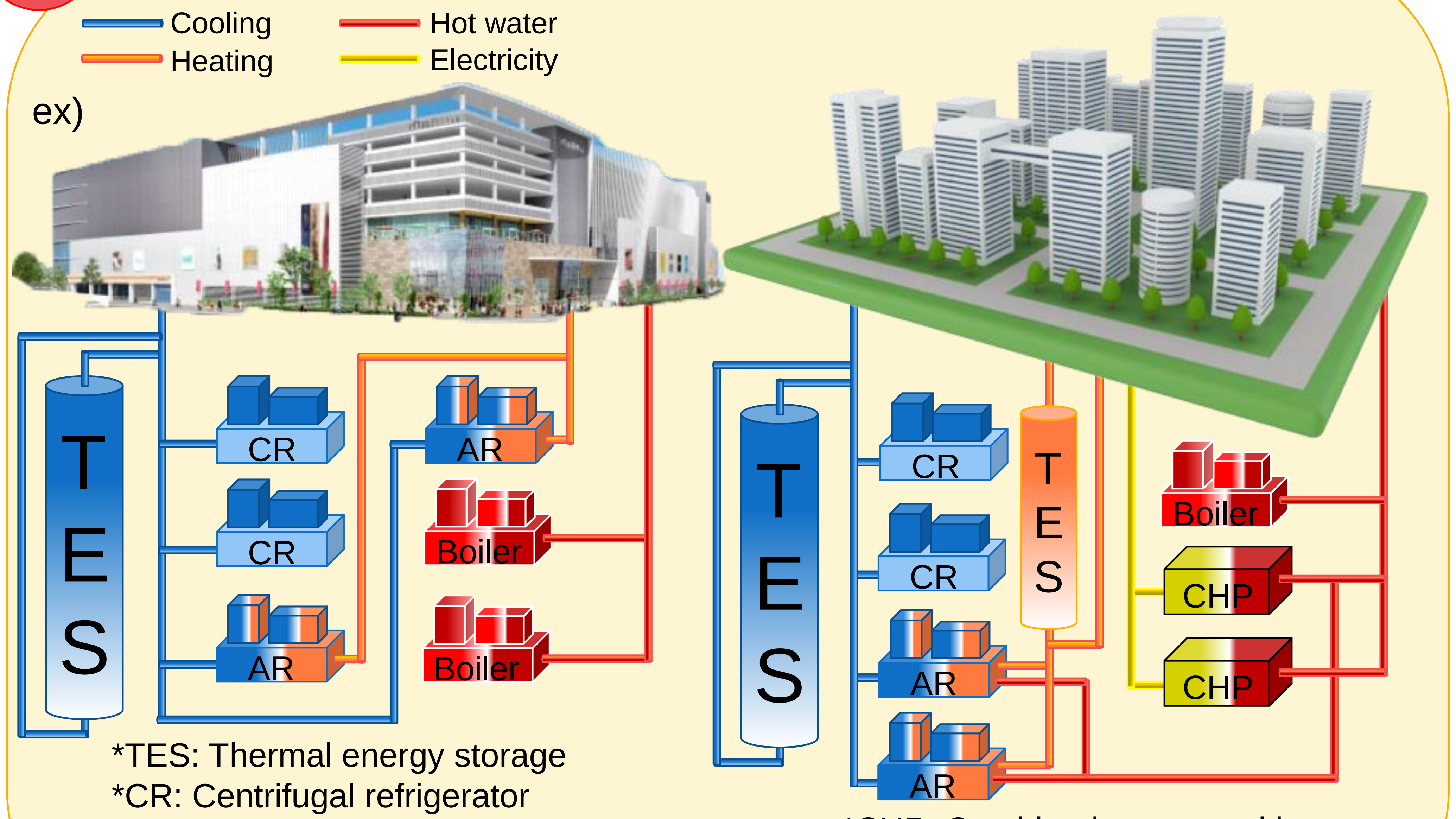
1 What is “operating optimization”?

It is to decide following issues:

1) Which machines should be worked?
2) When start and stop the machines?
3) How much heat should be generated?

It is not difficult to be applied to a simple system though,…

2 It is hard to be used in complex systems



*TES: Thermal energy storage
*CR: Centrifugal refrigerator
*AR: Absorption refrigerator

*CHP: Combined power and heat

Building energy system

District heating and cooling

3 What should we do?

1) Development of optimization methods for complex system
2) Incorporation of the methods in practical use

4 Development of optimization methods

- Significant functions of the methods

1) Rapid calculation for real-time controls
2) High accuracy of a given result
3) Adaptability

i. Un-limitation of machine’s configurations
ii. User friendly to set some parameters
iii. Incorporation of unsteady calculations

5 Key technology: Artificial intelligence

Artificial intelligence, especially metaheuristic optimization methods and neural networks, has required characteristics mentioned above.
We focused on εDE-RJ(epsilon constrained differential evolution with random jumping) in this study.

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Optimization method

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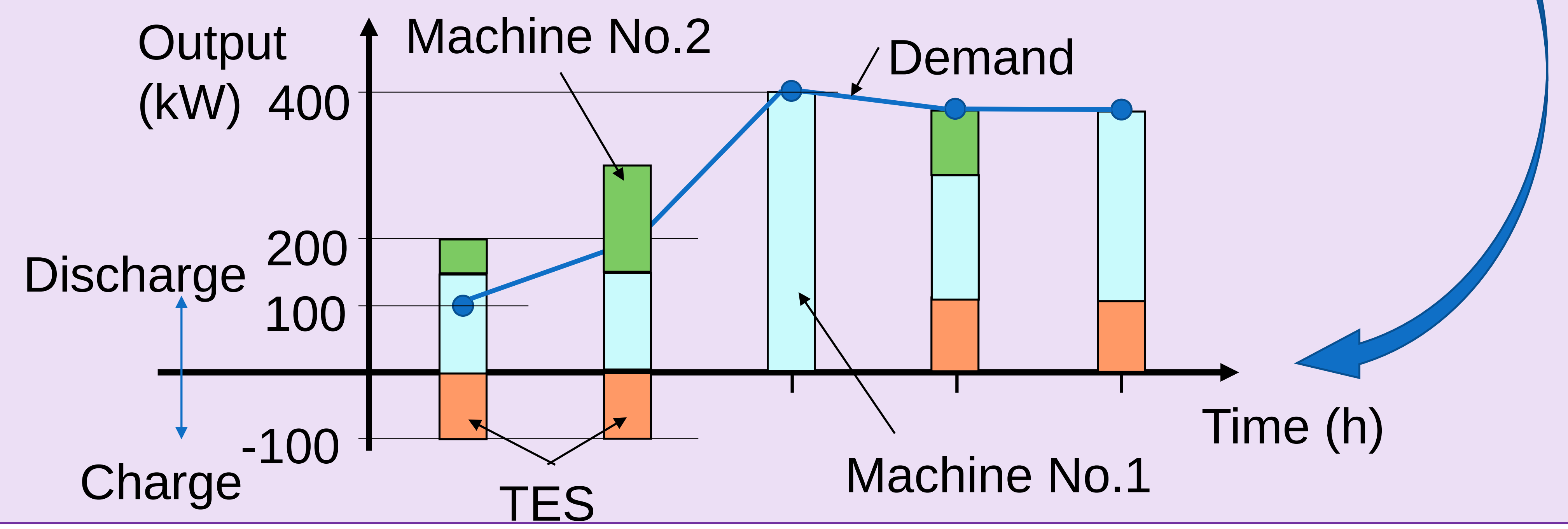
What is εDE-RJ (Epsilon differential evolution with random jumping)?

Search a solution	Differential evolution (DE)
	+
Solve constraints	Epsilon (ε) constraint method
	+
Avoid local optimum	Random jumping (RJ)

Problem formulation

N_{pop} Individual

	Schedule of TES					Schedule of machine No.1				
	1	2	3	4	5	1	2	3	4	5
Individual	-100	-100	0	100	100	150	150	400	200	370
Individual	0	-100	-100	50	150	100	300	500	350	250



Algorithm of DE and RJ

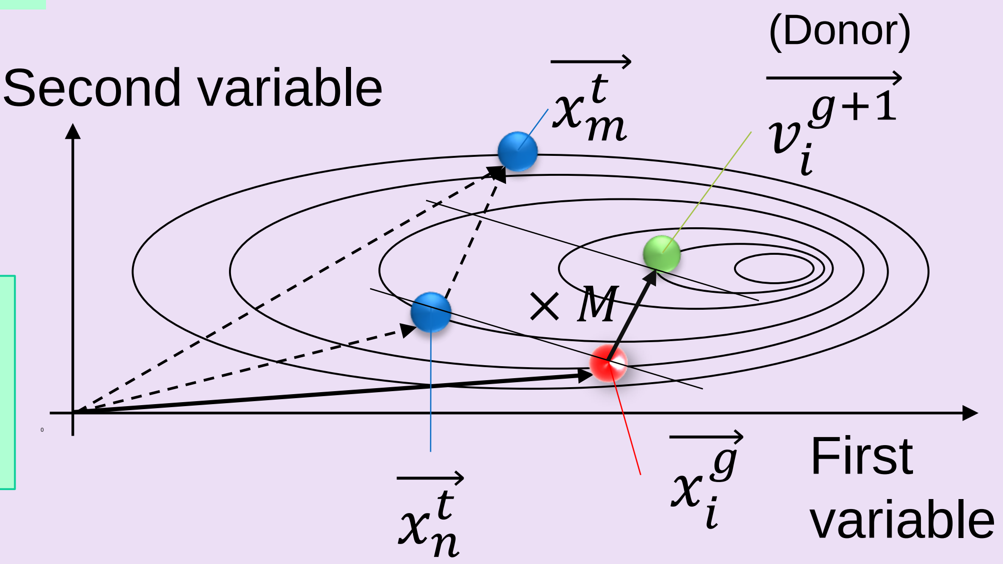
1. Initialization: Individuals ($N_{pop} = 100$) is randomly generated
2. Evaluation of each individual
3. Create new individuals by mutation and crossover methods
    1) Iteration of individuals, $x_i (i = 1, \dots, N_{pop})$
    2) Selection of two individuals ($x_m, x_n (m \neq n \neq i)$)
    3) Donor individual: $\overrightarrow{v_i^{g+1}} = \overrightarrow{x_i^g} + M\left(\overrightarrow{x_m^g} - \overrightarrow{x_n^g}\right)$, M: mutation rate(=0.5)
    4) Crossover: Applied random jumping

Crossover rate=0.7

$Rand$	0.23	0.87
$\overrightarrow{x_i^g}$	0.78	0.23
$\overrightarrow{v_i^{g+1}}$	0.82	0.23
$\overrightarrow{x_i^{g+1}}$	0.82	0.87

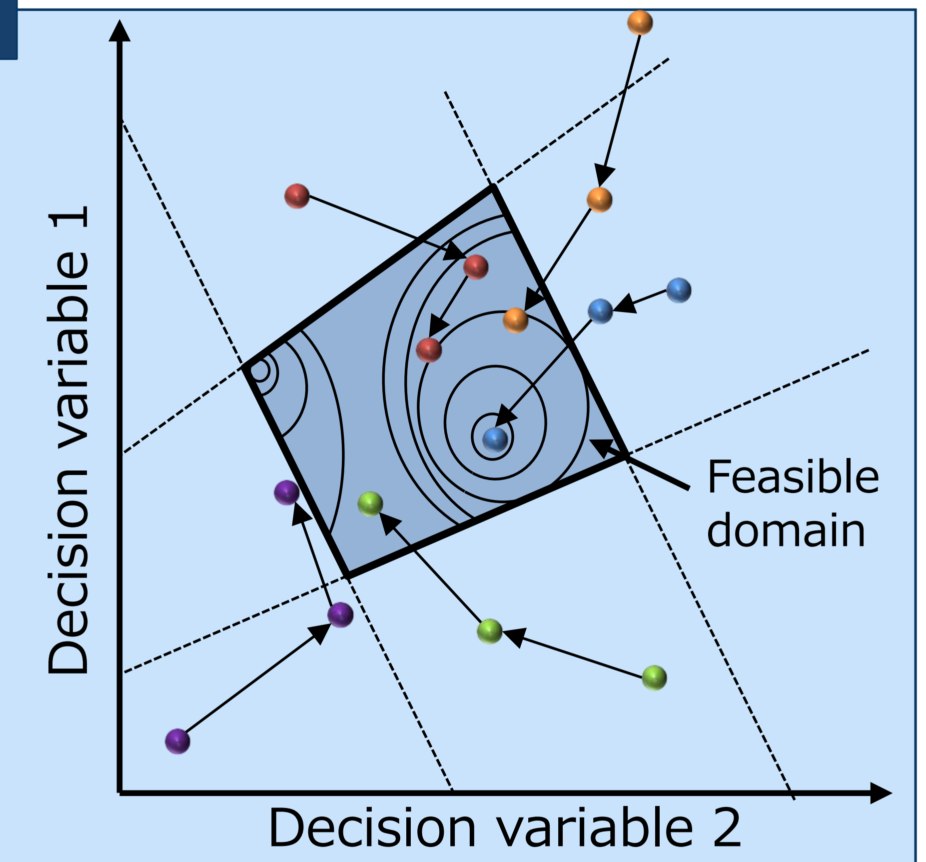
The same values

Replace by uniformly random number



Algorithm of ε constrained method

1) Initialization of ε(=1)
2) Calculation of constraint violation (φ) and objective function (f)
3) Replacement of individuals by comparison of φ or f as follows:
    i) Comparison of f_i^g and f_i^{g+1} when $\varphi < \varepsilon$.
    ii) Comparison of φ_i^g and φ_i^{g+1} when $\varphi \geq \varepsilon$.
6) ε decreases exponentially
7) Return to 1)



Conceptual diagram of ε constraint method

Optimal operation of complex energy system

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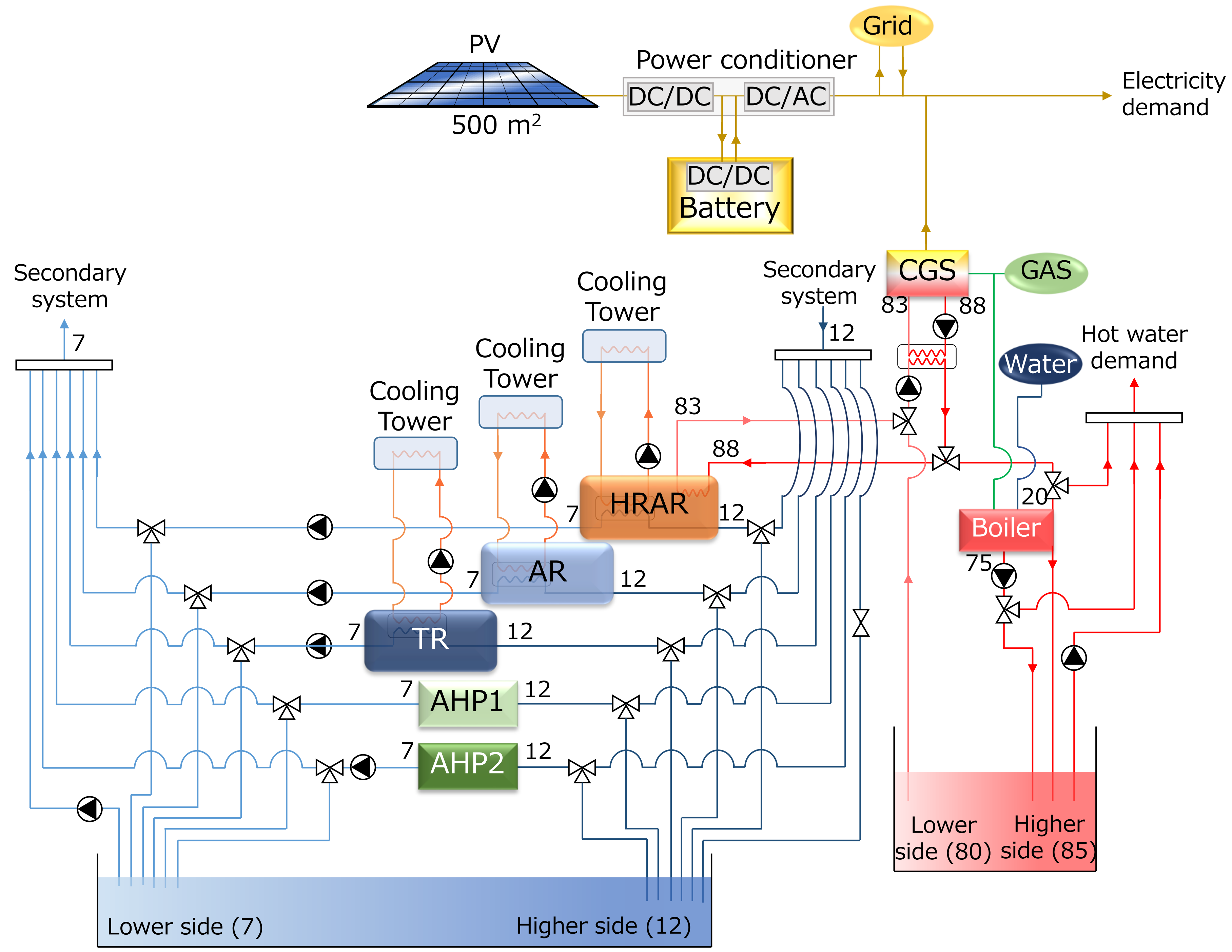
Objective function: daily operating costs

1 Benefits: rapid calculation of εDE

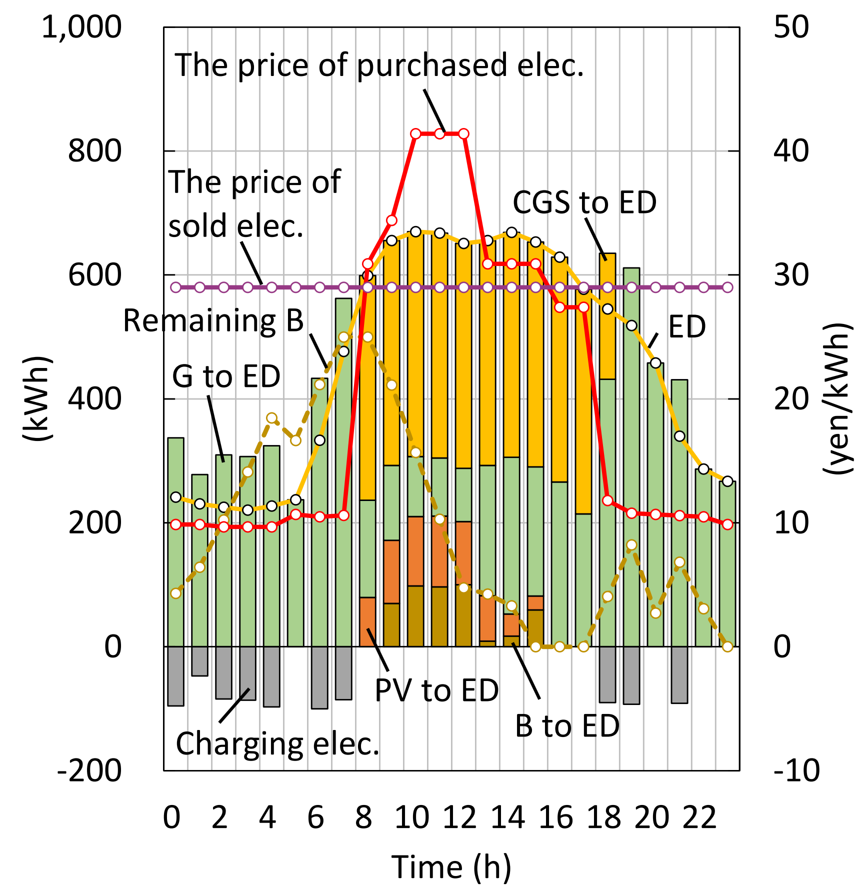
- Although the number of decision variables was 336 with nonlinear configuration, computation costs was just 6 min on an ordinal PC.
- Powerful advantage: computational complexity of εDE does not depend on the number of decision variables.
- εDE could incorporate variations of water temperature.

2 Optimal operating schedules

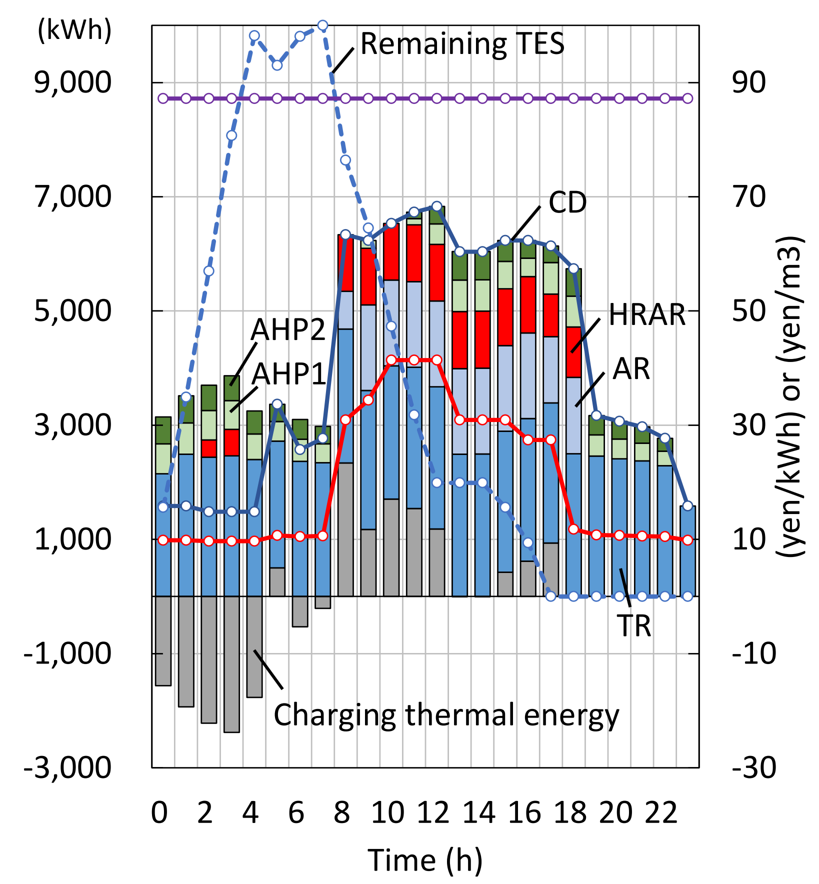
- CHP worked during daytime because of high electricity costs.
- Partial load rate of AHP1 and AHP2 were almost the same.
- Above result was optimal solution based on the mathematical theorem such as Lagrange multiplier method.



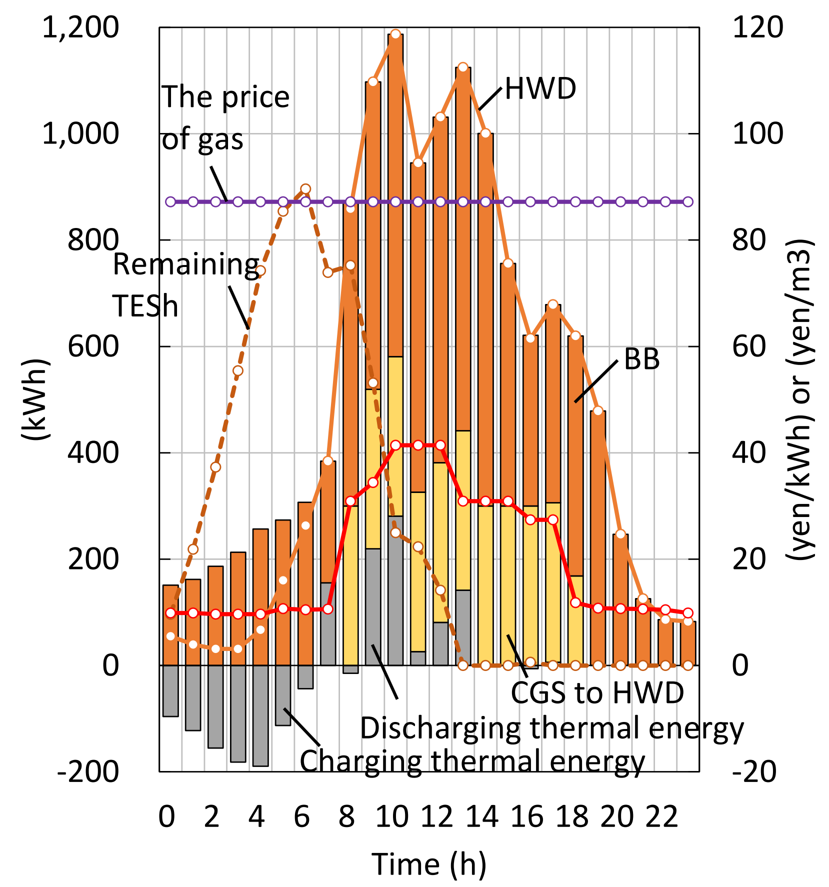
Energy system configuration



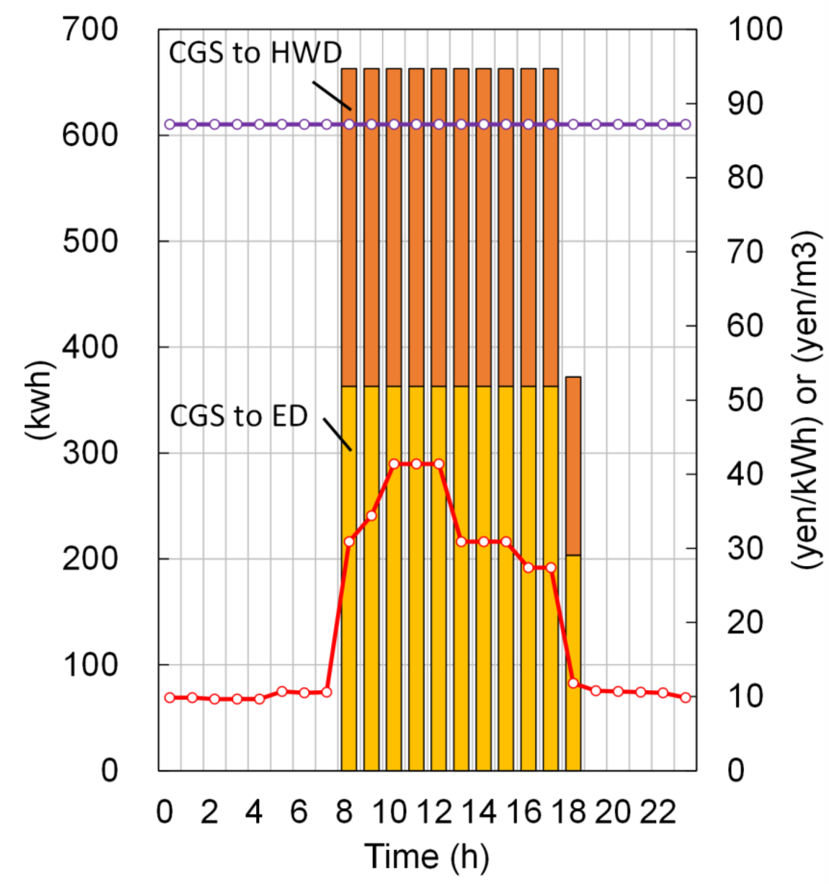
Optimal operation: Electricity system



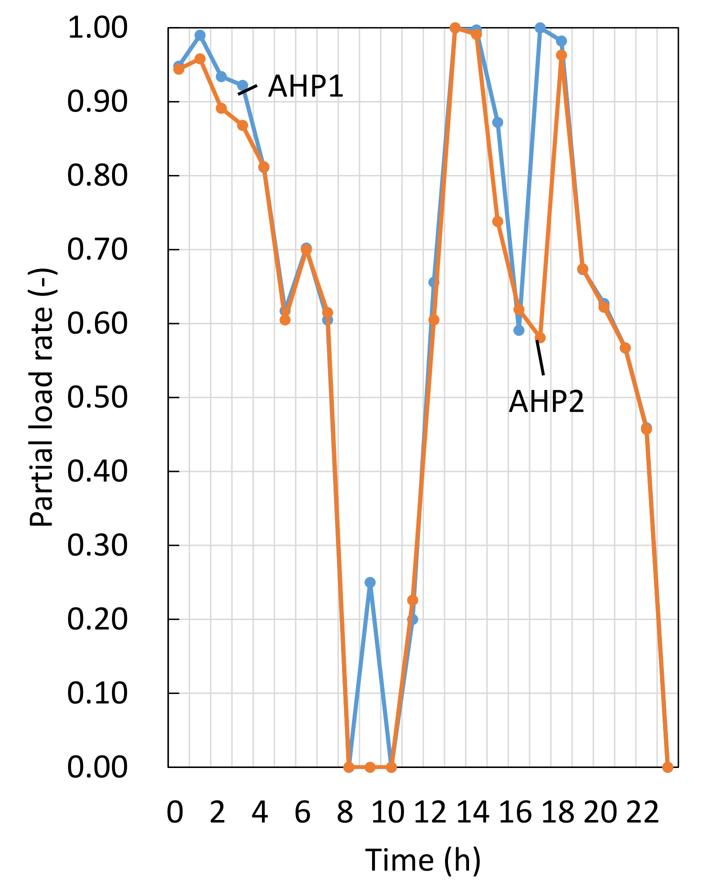
Cooling system



Hot water system



CHP



Partial load rate of AHPs

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Optimization of a district cooling system using ANN and εDE-RJ

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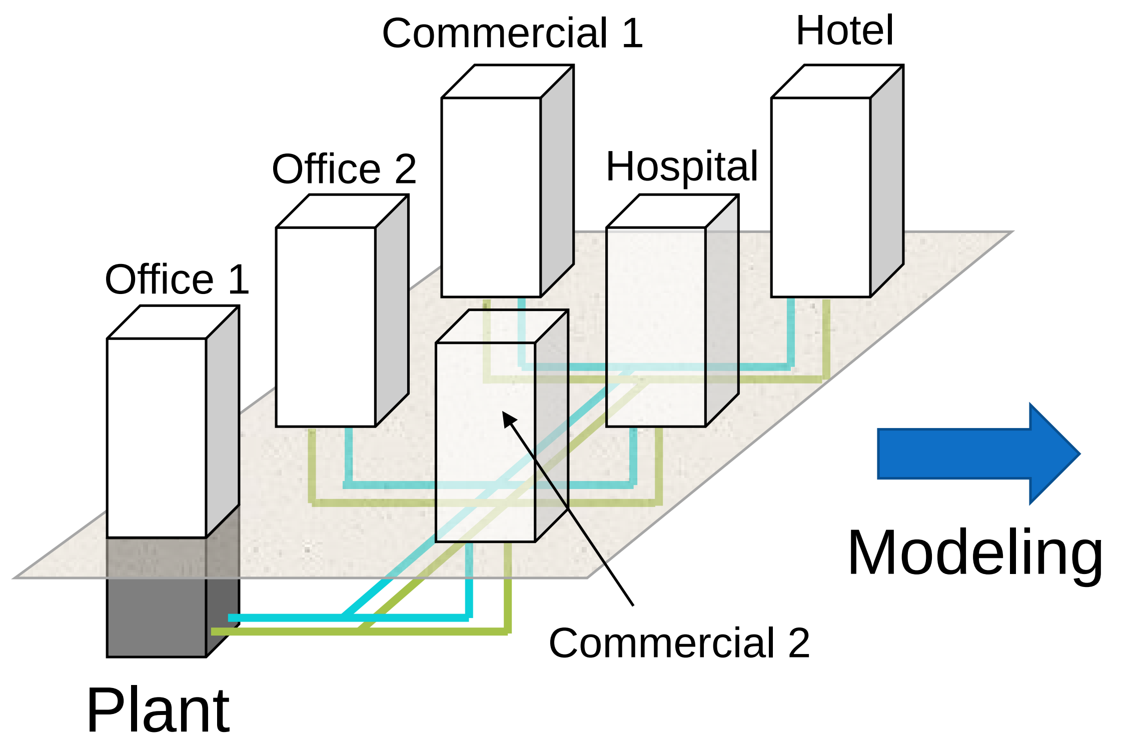
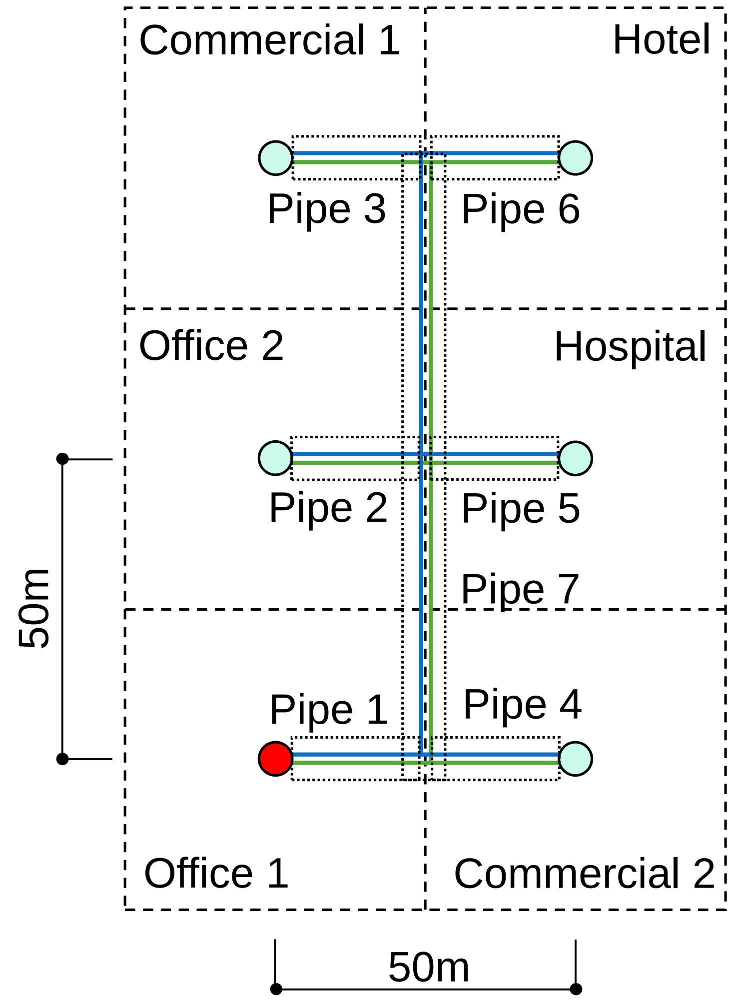
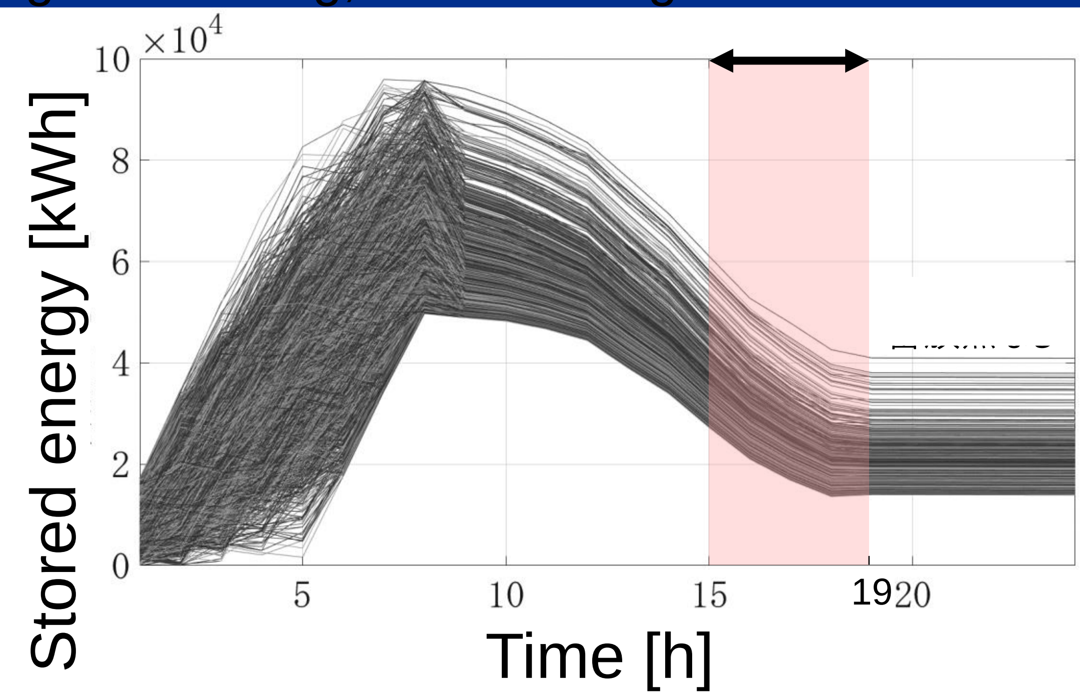


Conceptual diagram of a district



Location of buildings

- Neural network is used to predict bottom temperature, the same meaning as outlet temperature of TES, to reduce computation costs instead of physical model of stratified TES.



TES operations

Input data No1.

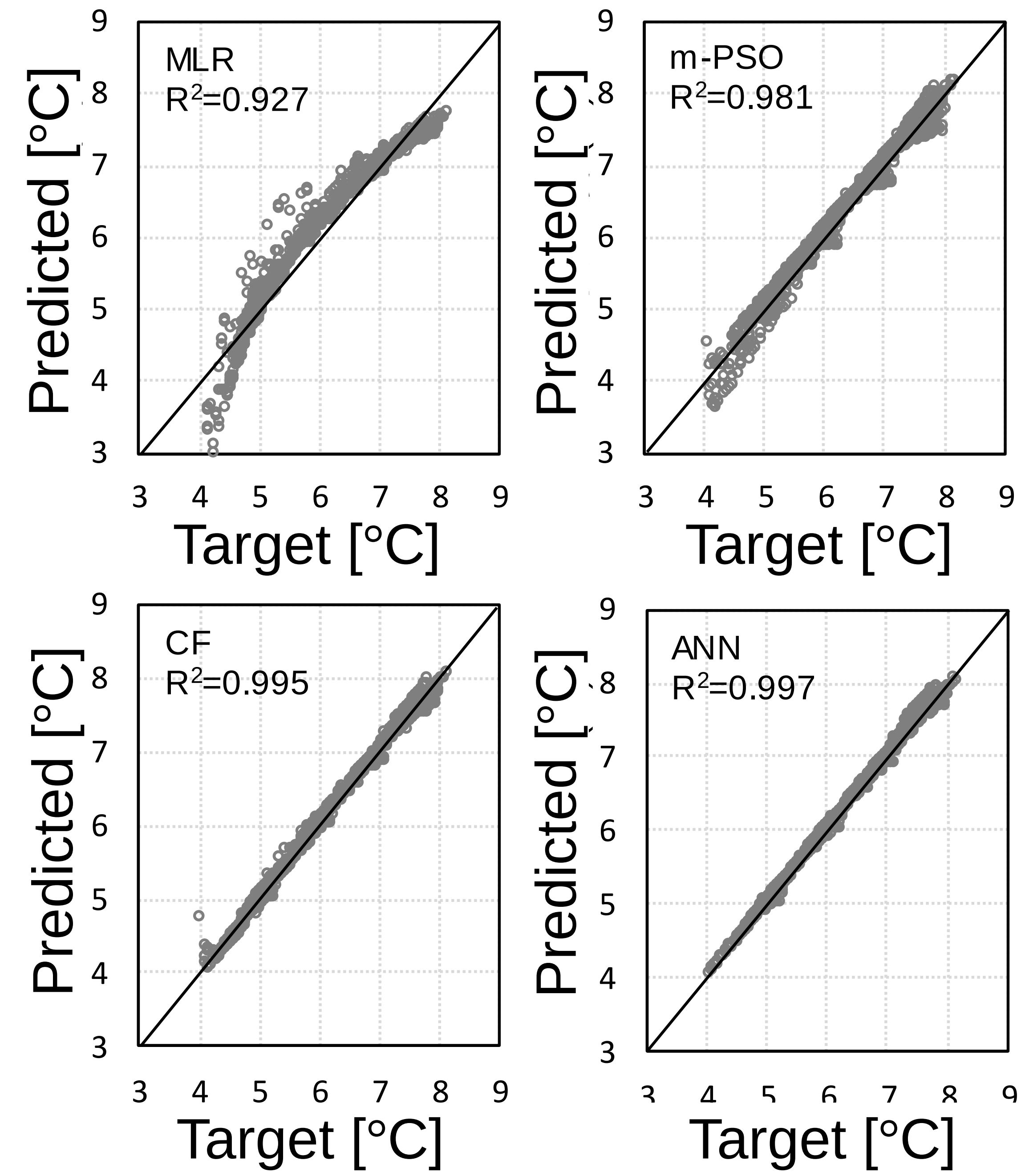
Maximum stored energy, H_M(kWh)

Input data No.2

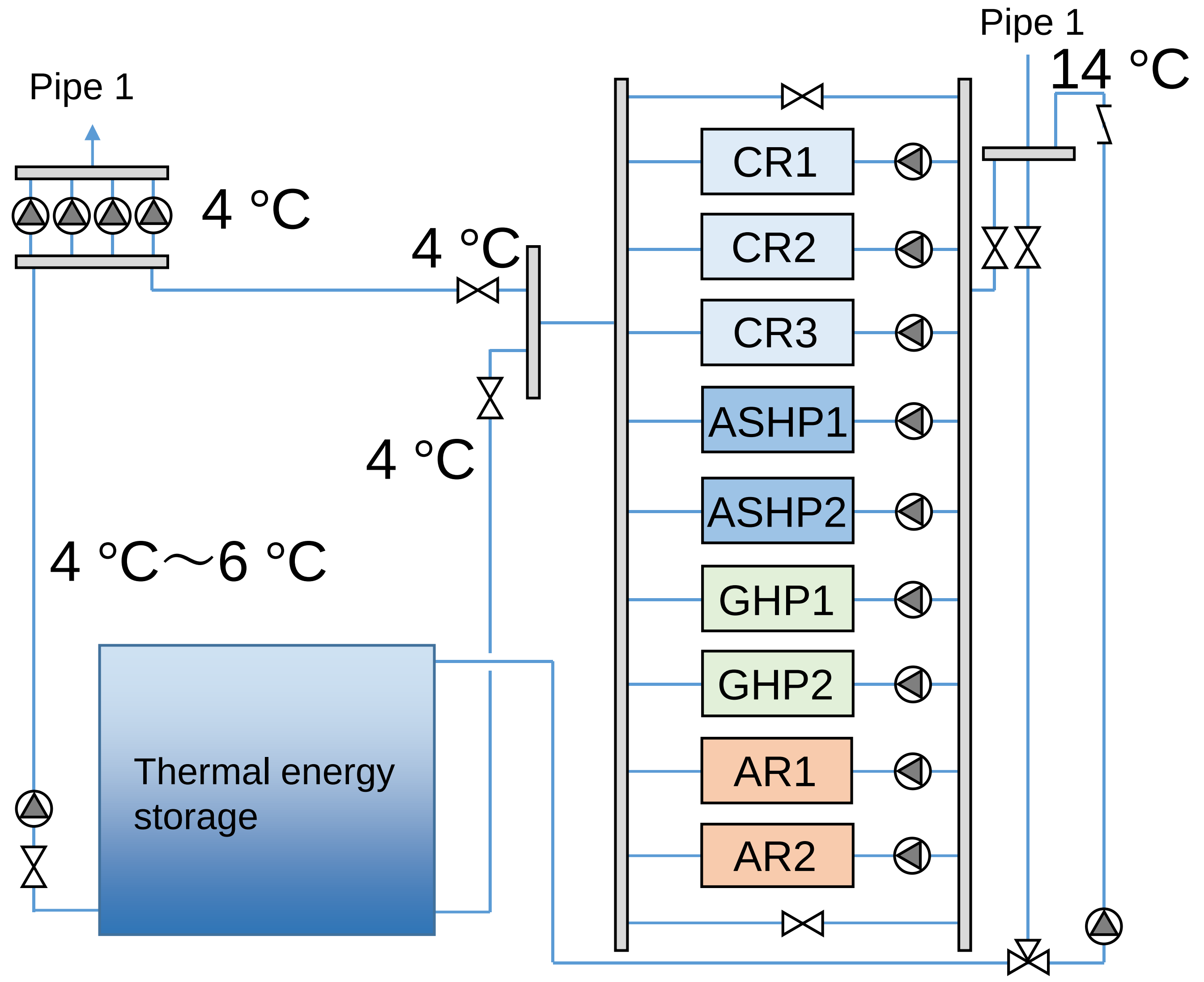
Stored energy at time step t, H_R^t(kWh)

Output data

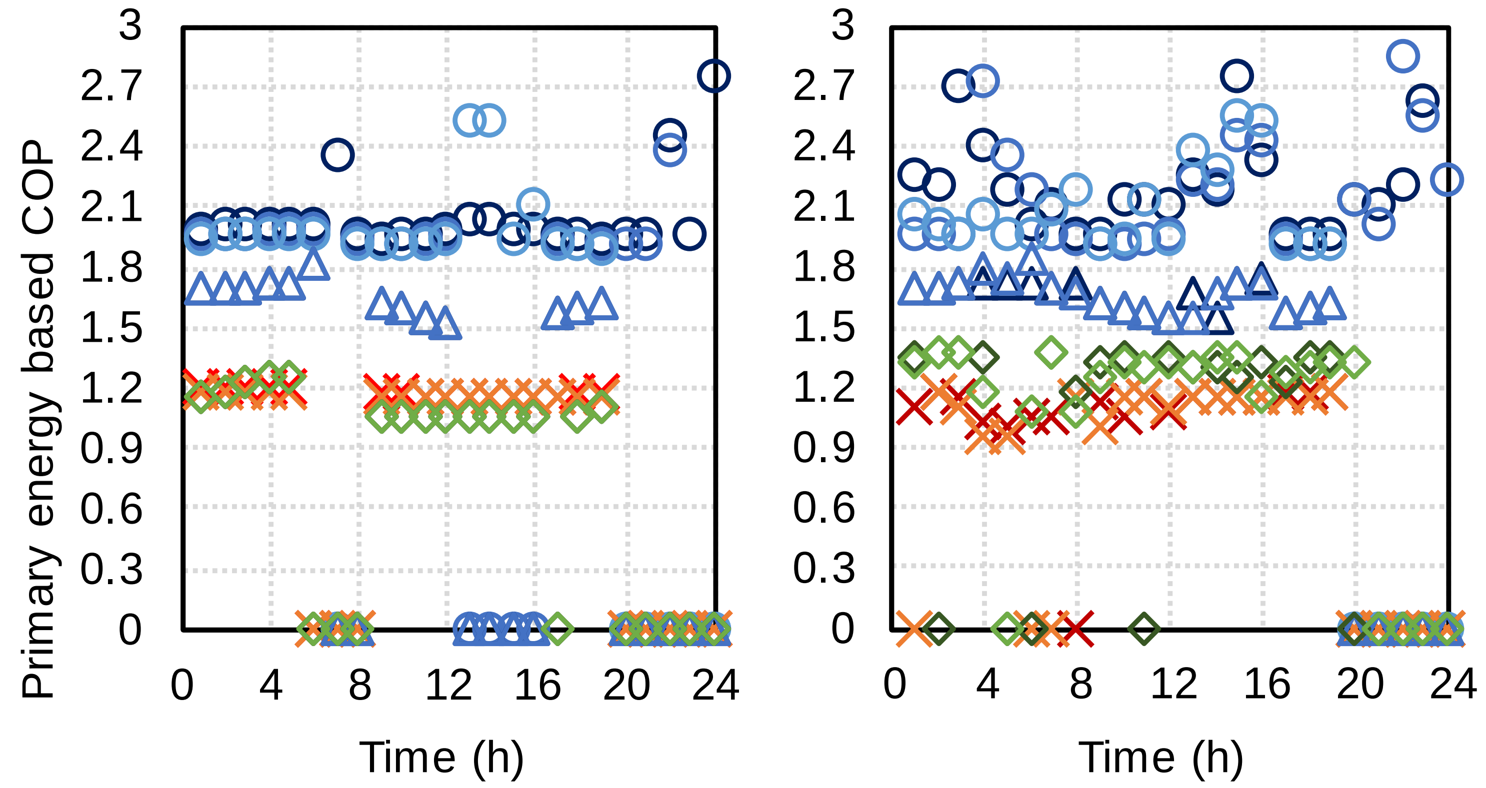
Bottom temperature, T_{20}^t [°C]



Comparison of results of each regression model



Energy system configuration



Comparison of COP in two cases

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