Faculty of Automation and Computer Science

Data Centers heat reuse in nearby neighborhoods: from air to liquid cooling

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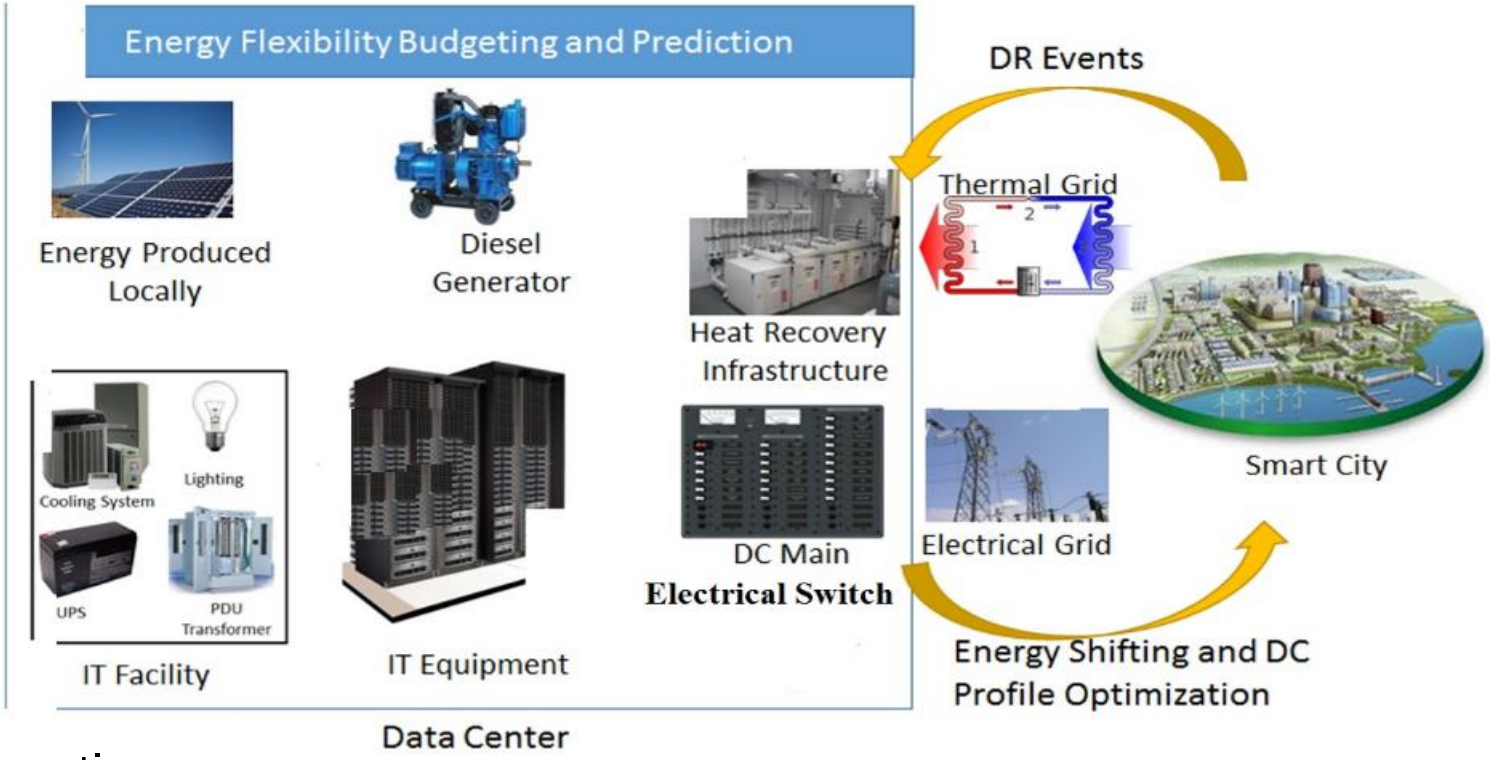
Presentation Outline

- Context and Motivation
- Heat Reuse Scenario
- DC Thermal Model
- DC Flexibility Management and Optimization
- PD 2019 CoolDC Project

Context and Motivation

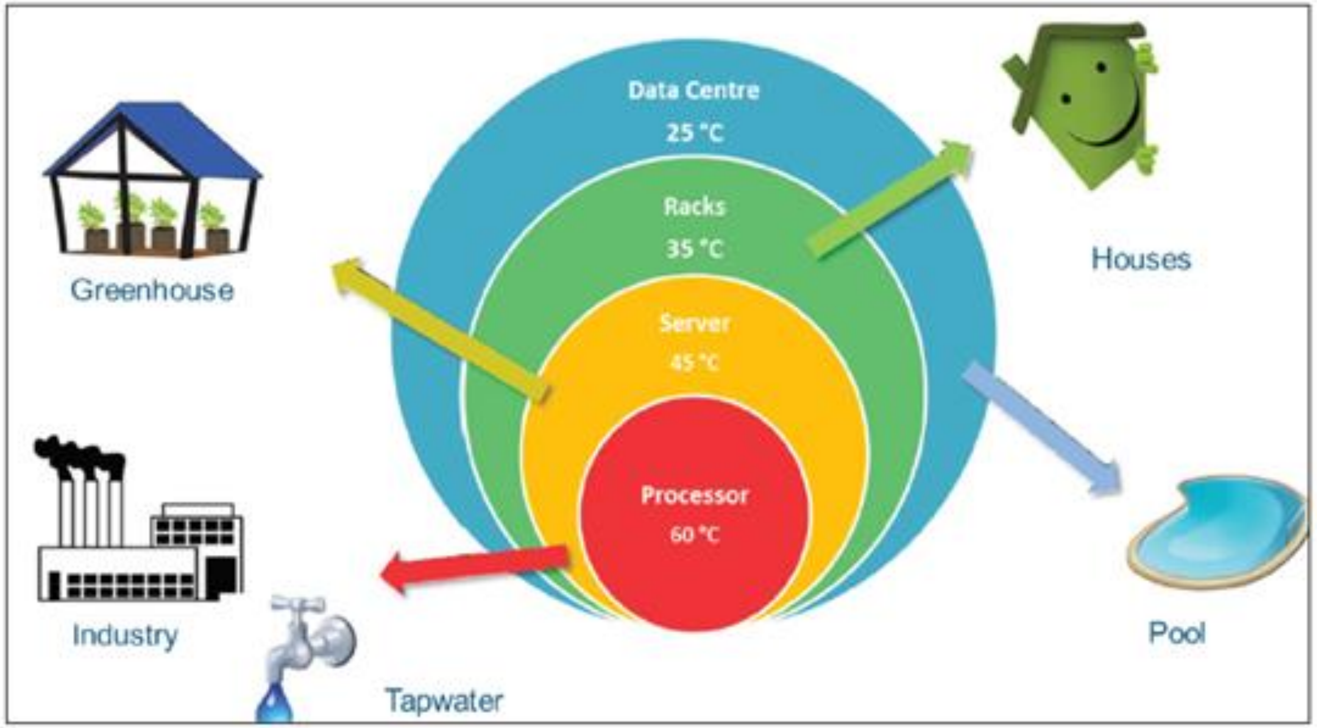
- DCs are large producers of waste heat
  - High potential of becoming thermal energy sources
  - Effectively used either internally for Space Heating and/or Domestic or District Heating network operators



- Smart thermal and energy grids integration
  - Achieve cost-effectiveness
  - Participation in demand response programs

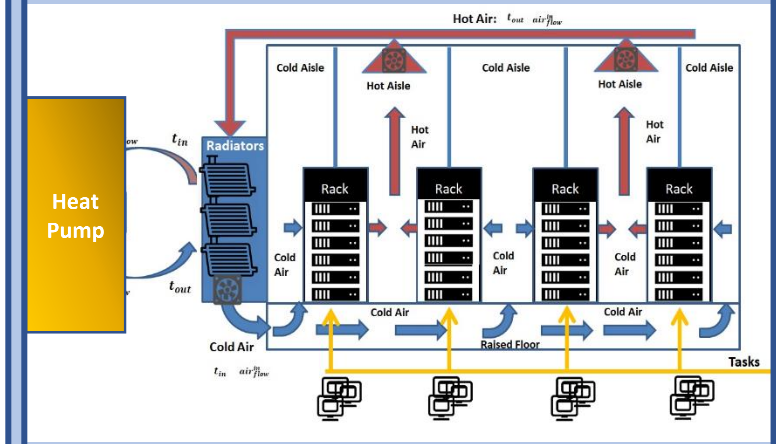
Heat Reuse Scenario

- Optimize DC operations to **deliver heat** to the local heat grid.
- Recover, redistribute and reuse DC residual heat for building space heating (residential and non-residential such hospitals, hotels, greenhouses and pools), service hot water and industrial processes.
- DC participates to the local Heat Marketplace trading heat and as such creating a new revenue source over longer period for the DC.
- In doing so, the DC achieves significant energy & cost savings, reduces its CO_2 emissions, contributes to reducing the system-level environmental footprint and supports smart city urbanization.

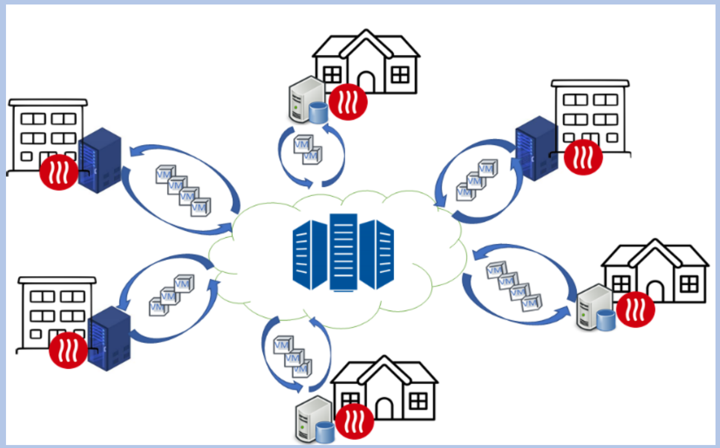


Heat Reuse Scenarios

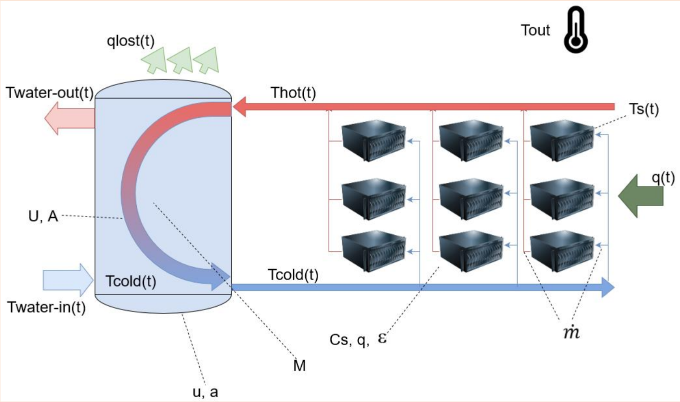
- Air-cooled DCs equipped with heat pumps sell heat to District Heating Operator



- Air-cooled Distributed DCs are used to heat households directly



- Liquid-cooled DCs:
  - Heat Home Boiler
  - Integrate with District Heat Operator
  - Water Heating (e.g., swimming pools)



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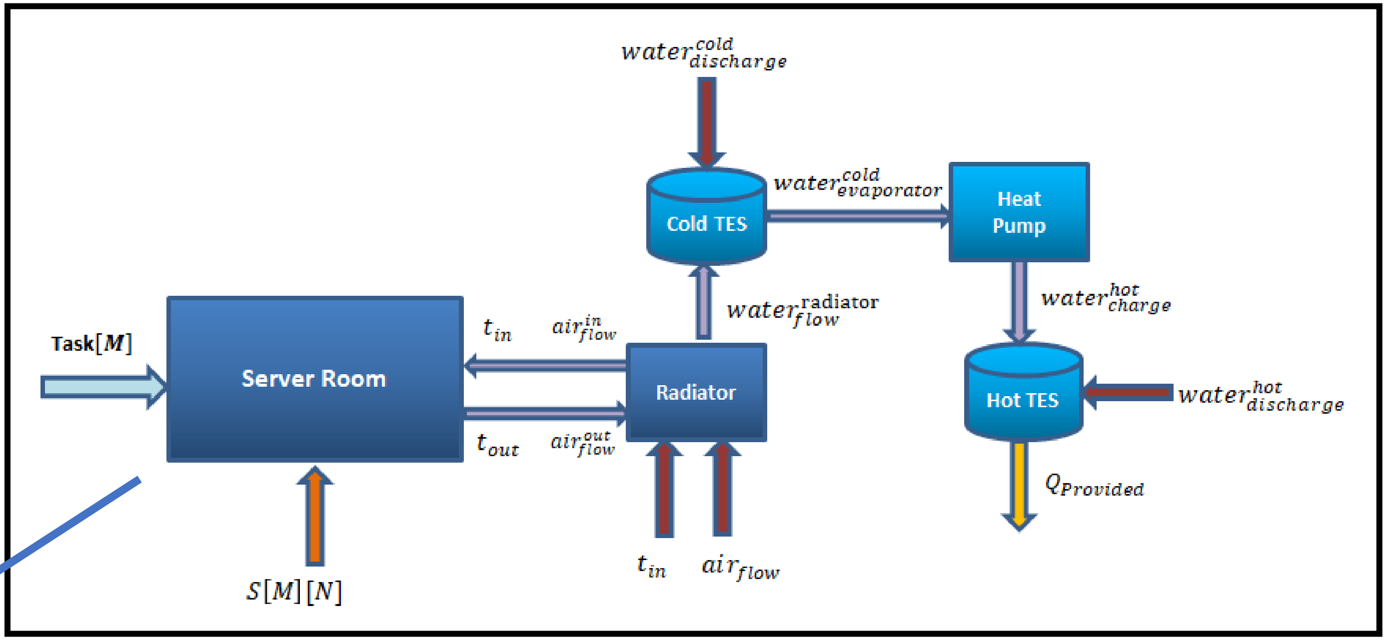
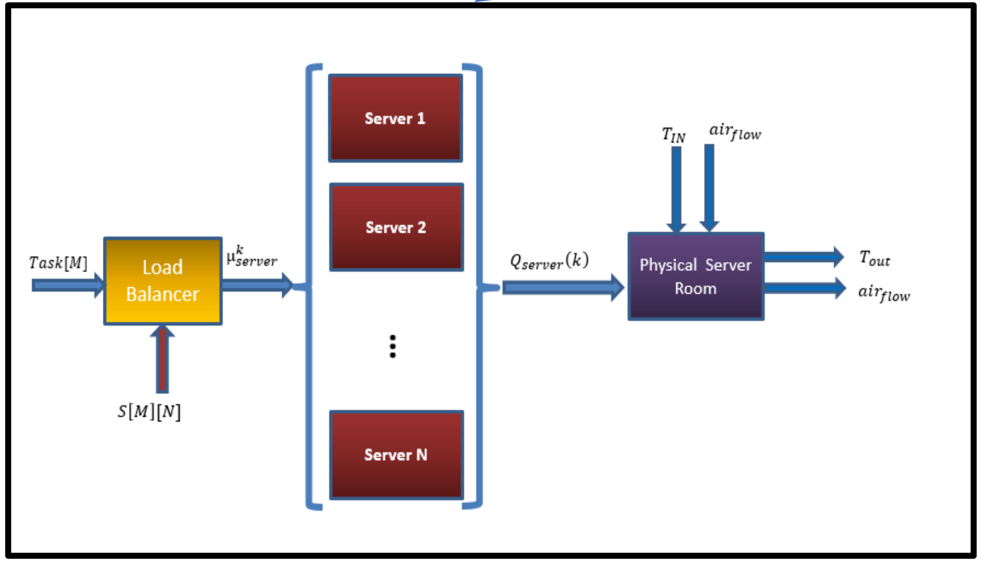
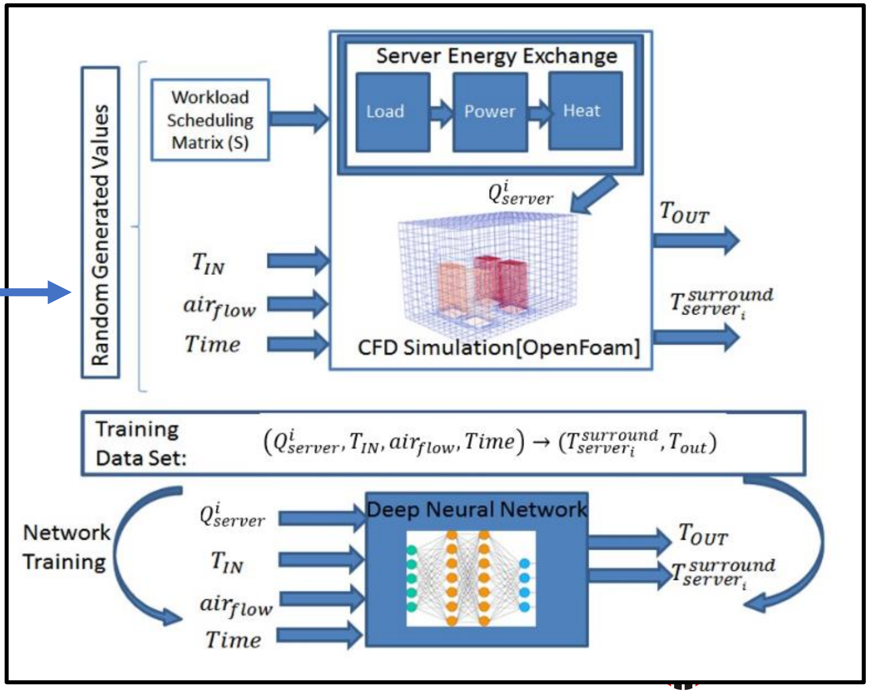
Air-Cooled DC Thermal Model

- Develop **a Digital Twin** of the Internal processes of the DC to allow proactive control and planning
- Use a System-of-Systems recursive modeling methodology







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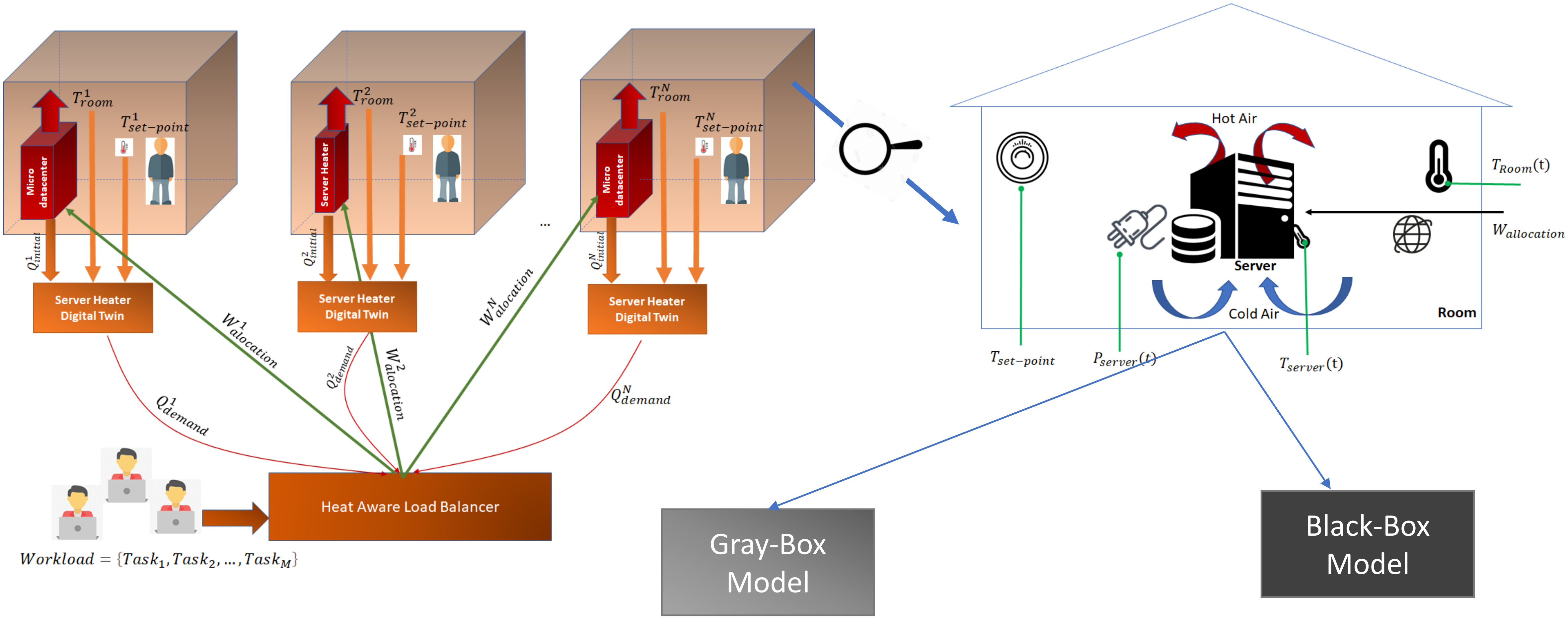
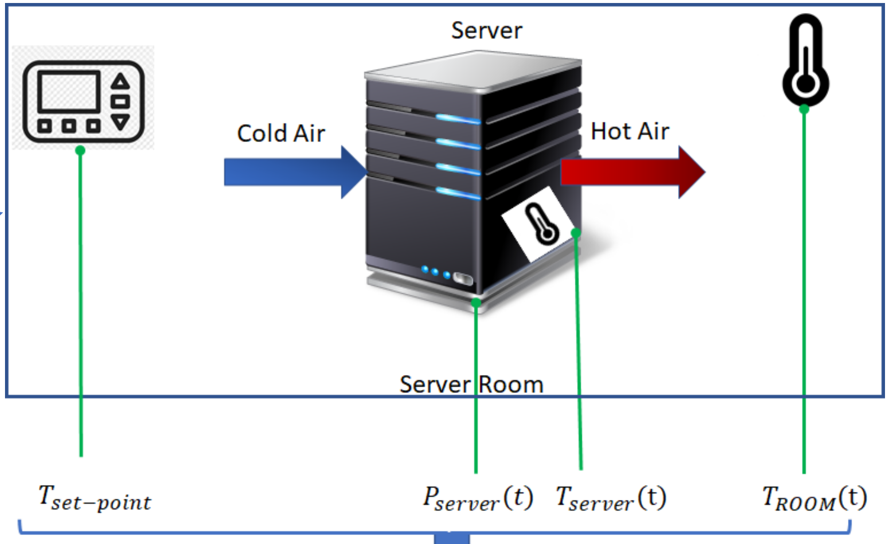
Distributed Air-Cooled DC Thermal Model



$$Q_{Demand}(\mathrm{t}) = \frac{P_{loss} + \frac{M \times c_a \times (T_{set-point} - T_{ROOM})}{\Delta t} - P_{server}(0)}{\nabla} \times t + P_{server}(0)$$

Distributed Air-Cooled DC Thermal Model

Black-Box Model



Monitor Data

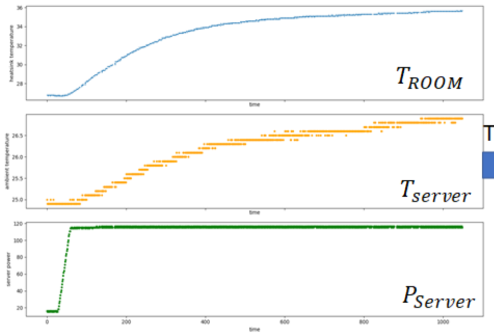
Monitored data

$$t_1 \rightarrow T_{set-point}(t_1), P_{Server}(t_1), T_{server}(t_1), T_{ROOM}(t_1)$$
$$t_2 \rightarrow T_{set-point}(t_2), P_{Server}(t_2), T_{server}(t_2), T_{ROOM}(t_2)$$
$$\vdots$$
$$t_n \rightarrow T_{set-point}(t_n), P_{Server}(t_n), T_{server}(t_n), T_{ROOM}(t_n)$$

Determine relevant samples by applying correlation factor

Pearson's Coefficient

$$r^{window}_{T_{server},T_{ROOM}} = \frac{cov(T_{server}, T_{ROOM})}{\sigma_{T_{server}} \sigma_{T_{ROOM}}} > threshold$$



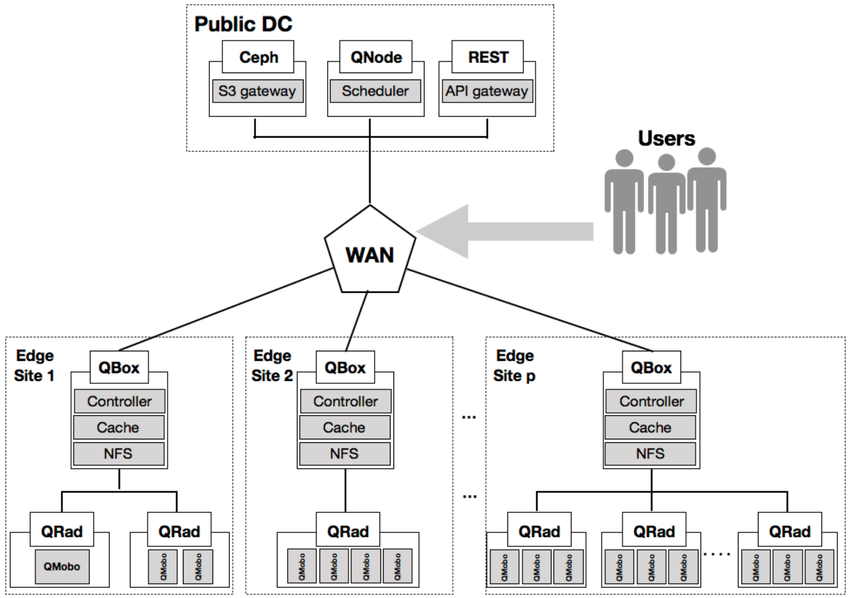
Generate Training Data

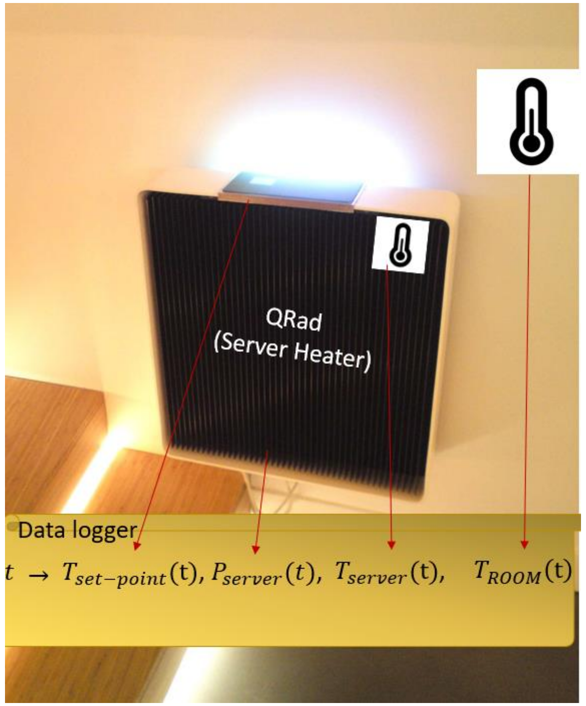
$$T_{ROOM}(t_1), P_{server}(t_1), T_{server}(t_1) \rightarrow P_{server}(t_1+1) \dots P_{Server}(t_1+T)$$
$$T_{ROOM}(t_2), P_{server}(t_2), T_{server}(t_2) \rightarrow P_{server}(t_2+1) \dots P_{Server}(t_2+T)$$
$$\vdots$$
$$T_{ROOM}(t_n), P_{server}(t_n), T_{server}(t_n) \rightarrow P_{server}(t_n+1) \dots P_{Server}(t_n+T)$$

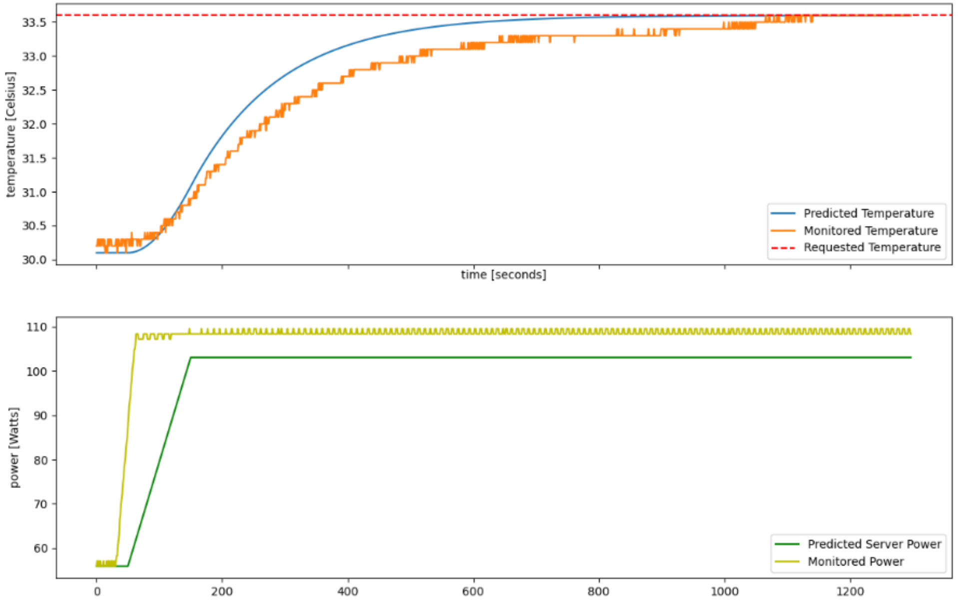
Model Type	Model Description
Linear Regression	The basic linear regressor was used to determine the baseline for prediction accuracy
Polynomial Regression	A second-degree polynomial regressor. Multiple degrees were considered, but the validation score began to drop after the degree was set to 2.
Gradient Boosted Regression	90 estimators with a maximum depth of 4. The samples had a minimum split of 5 and the learning rate was 0.1. The loss was computed using the least-squares method.
Random Forest Regression	9 estimators with a maximum depth of 4 are defined.
Support Vector Regression	A support vector regressor with kernel type of radial basis function and parameters: $C = 100, \gamma = 0.01, \varepsilon = 0.1$
K Neighbors Regression	The K-Nearest Neighbors Regression with 2 neighbors and uniform weights.
Deep Learning Regression	Multi-Layer Perceptron having one input layer, two hidden layers of 128 and 256 neurons, and one output layer. The activation function for the hidden layers is of type Rectified Linear Units (ReLU), and 500 epochs were used for training. The loss function was the mean squared error and the optimizer ADAM. Early stopping was employed with the patience of 50 epochs and a minimum validation loss as the monitor.

Distributed Air-Cooled DC Thermal Model

Test case distributed DC - Qarnot Distributed DC

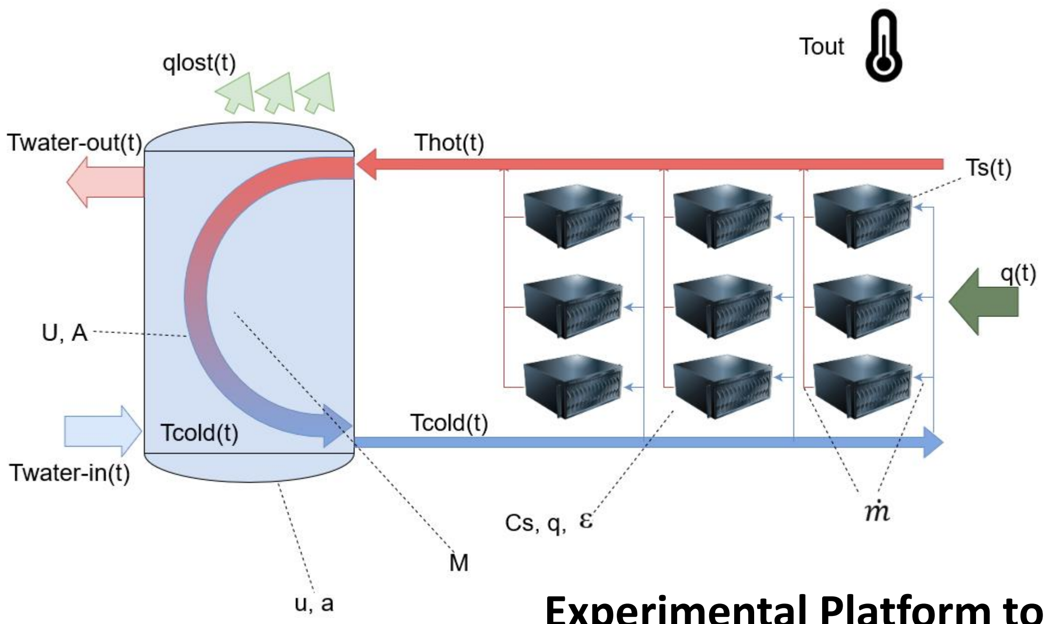






Model	RMSE	R2	Error Mean	Error Standard Deviation	RMSPE	MAPE
Linear Regressor	14.4.	0.89	−0.66	14.04	8.62	13.36
Polynomial Regression	33.12	0.39	2.05	29.19	23.38	13.65
Random Forest Regressor	10.04	0.92	−2.06	9.55	7.6	5.06
Gradient Boosting Regressor	10.65	0.94	−1.12	10.32	7.14	4.74
Support Vector Regression	16.28	0.85	2.33	15.02	9.71	6.89
K Neighbors Regressor	13.7	0.84	1.09	12.85	10.54	6.27
Multi-Layer Perceptron Deep Neural Network	33.09	1	1.92	24.54	20.62	17.29

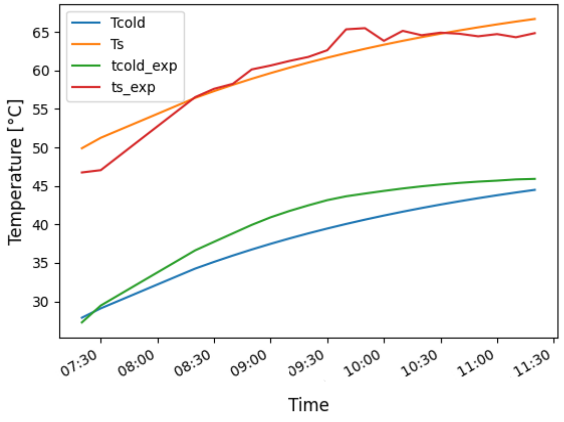
Liquid-Cooled DC Thermal Model



Gray-Box model to predict power-temperature correlation

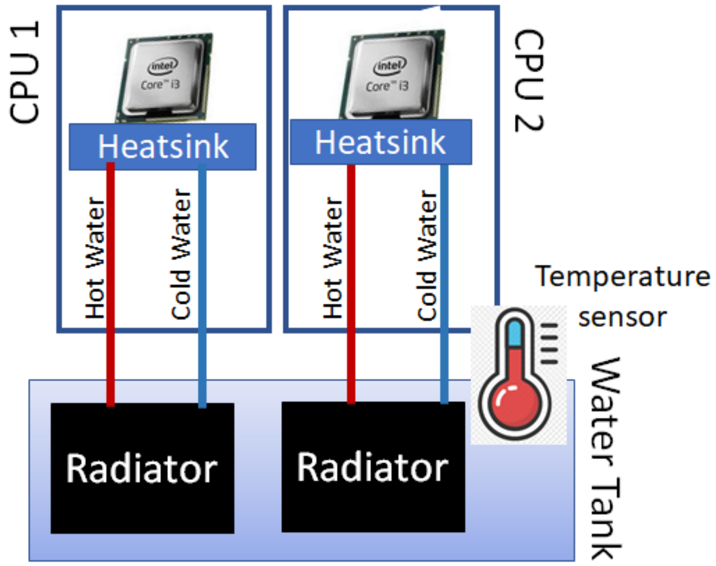
$$\frac{dT_s}{dt} = \frac{\dot{q} - \dot{m}c_{water}\varepsilon(T_s - T_{cold})}{C_s}$$

$$\frac{dT_{cold}}{dt} = \frac{[\varepsilon T_s + (1-\varepsilon)T_{cold}]UA + uaT_{out}}{Mc_{water}} - \frac{(UA+ua)T_{cold}}{Mc_{water}}$$



Experimental Platform to validate results

- FROSTFLOW 120 liquid cooling units on two PCs equipped with Intel i3 540 processors and 8 GB RAM memory.
- insulated vessel containing M=4 kilograms of water.
- set of temperature sensors
- 3-7% MAPE error for temperature prediction



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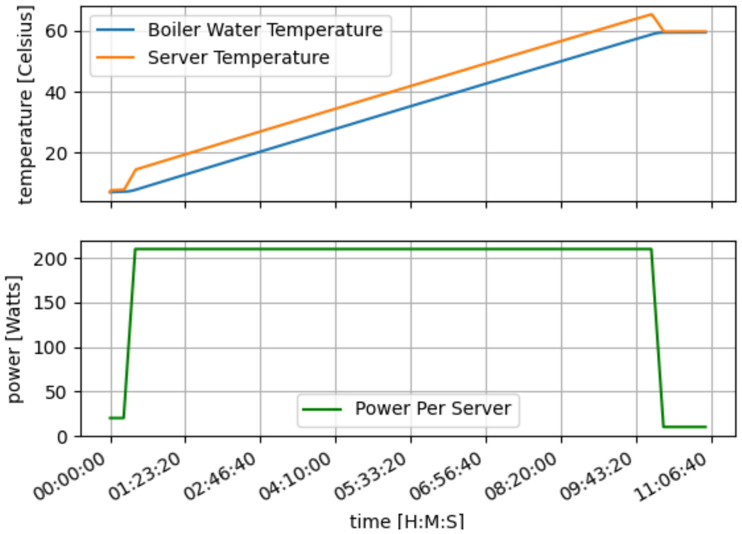
Liquid-Cooled DC Thermal Model

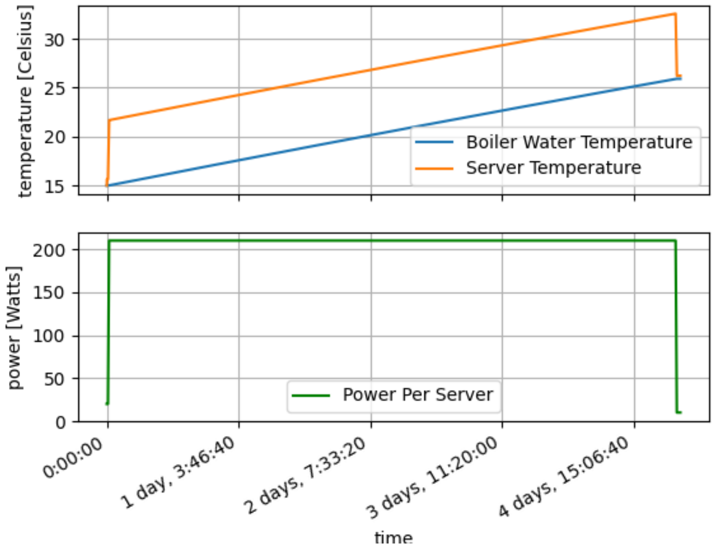
Feasibility Study - Household

We consider that M=150 kg of water is enough for a two-person household. This quantity fits into a cylindrical tank with a surface area of a=1.67 m^2. The helical pipe inside the server has approximatively A=1.2 m^2 external area where the heat exchange takes place. We have concluded that for initial and ambient temperatures of 7°C, using 9 processing units linked in parallel, 10 hours are needed for the tank water to reach 59.5°C, the maximum heatsink temperature being 65.47°C



Feasibility Study – Swimming Pool

A pool, with a capacity of M=30000 kg (approximately 30000 L) of water. Again, the water is place in an isolated tank, which this time has an external surface area of approximatively a=59.48 m^2 (a diameter of 3.92 m and a height of 2.87 m). As we would need 100 processing units, the piping's heat transfer surface area reaches approximatively A=4 m^2. Starting from an initial temperature of 15°C and an ambient temperature of 20°C, the processing units would need 120 hours to take the tank water's temperature to 25.9°C. Their heatsink temperatures would not exceed 32.57°C.



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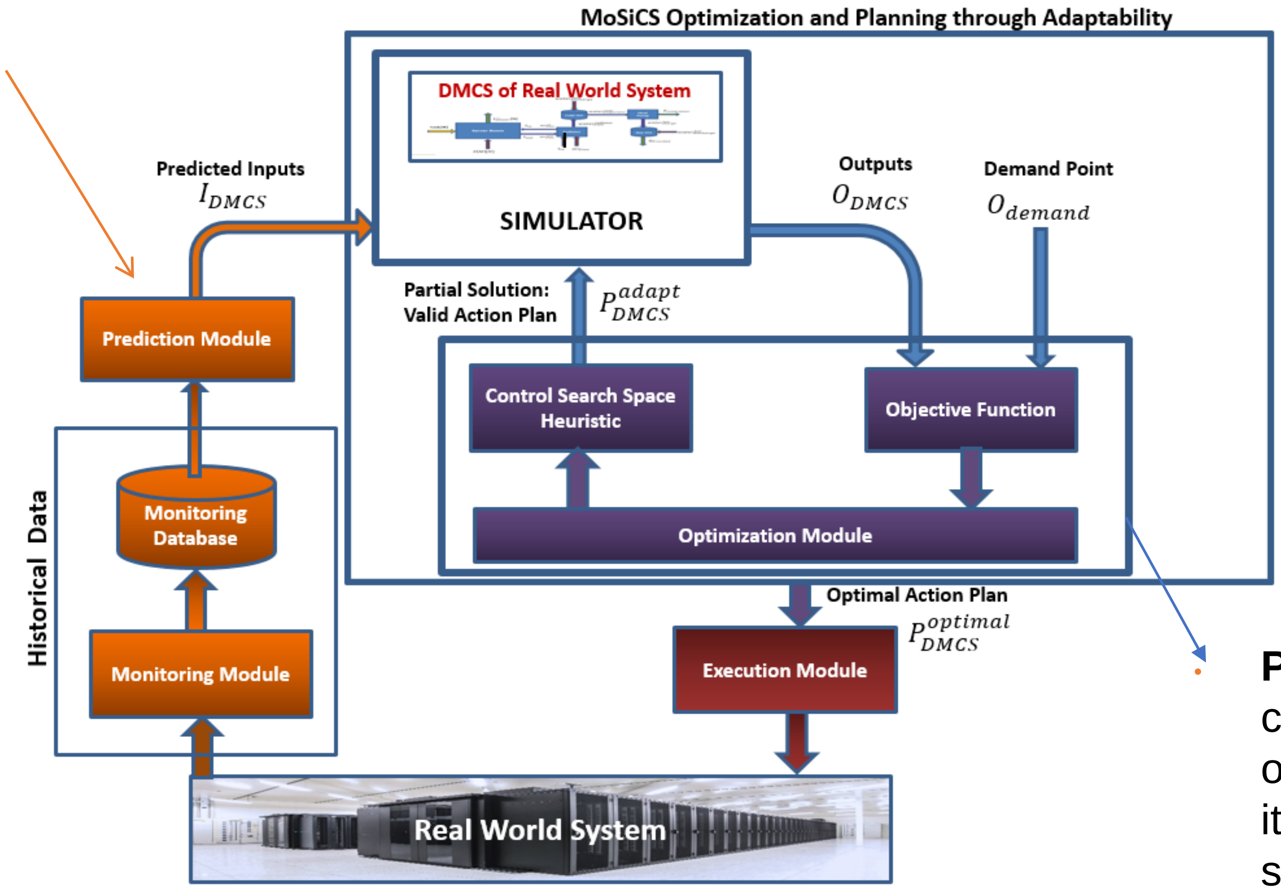
DC Flexibility Management and Optimization

- Self Adaptive Scheduler as an extension of the IBM MAPE-K architecture

- **Analysis Stage** computes predictions of the future system inputs based on historical data



- **Planning Stage** computes an optimal plan by iteratively simulating the DMCS model

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PD 2019 CoolDC Project

- Facilitate the transition to **liquid cooling systems**

- Project Objectives:
  - Study the correlation among workload distribution, temperature setpoints, thermal flexibility of DCs with liquid cooling and DH heat demand aiming to assess the heat re-use potential

  - Development of models for estimating the baseline heat profiles and forecasting the thermal flexibility of DCs featuring liquid cooling

  - Development of novel hybrid optimizer for thermal aware workload scheduling to shift thermal flexibility and maximize the quality of the heat to be re-used