Energy Optimal Control of Heating, Ventilation and Cooling Systems

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Beams Department Seminar Series

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NTNU and CERN Doctoral Degree Program

https://norway.cern/ntnu-cern-phd-projects?language=en

Project : Energy Optimal Control of Heating, Ventilation and Cooling Systems at CERN

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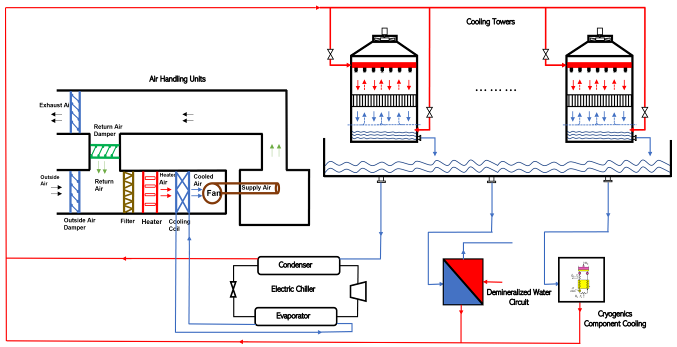
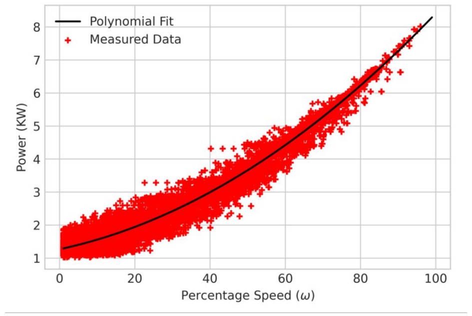
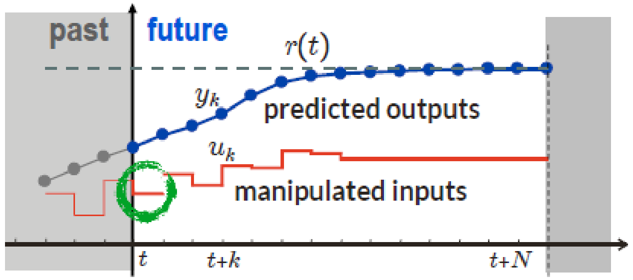
Outline of the Talk

Cooling Plants at CERN

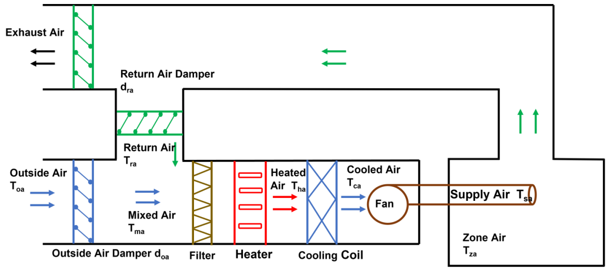


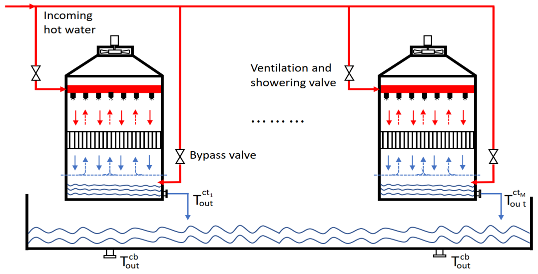
Energy Optimal Control





Case Studies

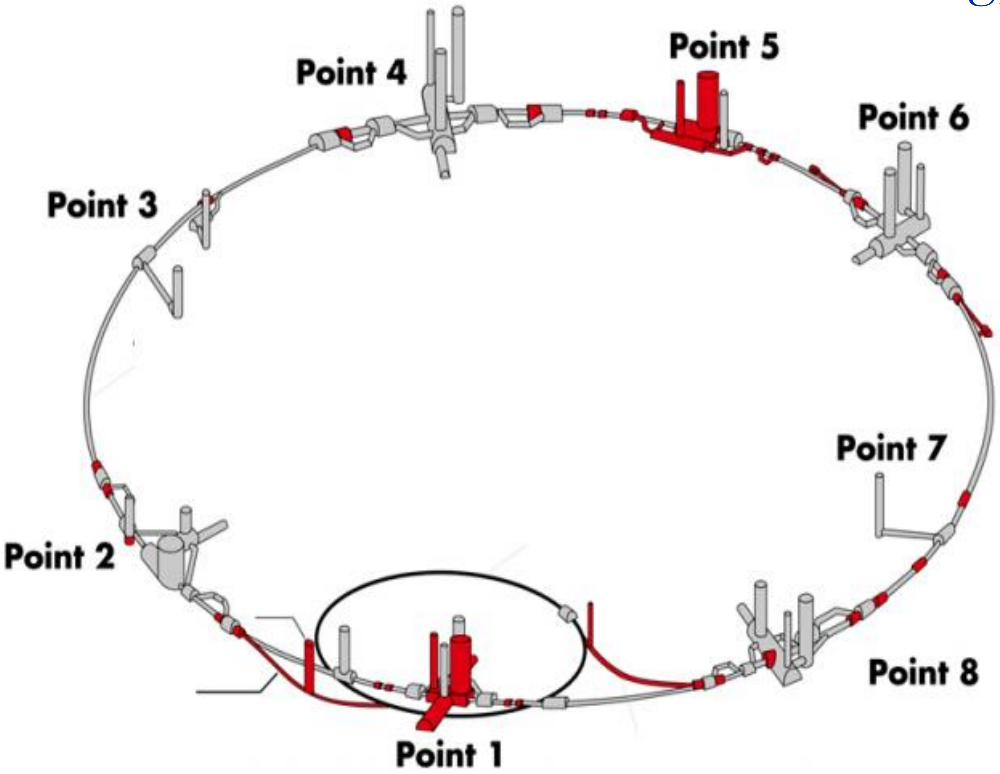




Cooling Plants at CERN

- CERN has many large scale cooling plants at different points of the LHC ring to meet the cooling demands of different clients.

- Cooling plants are one of the main consumers of electrical energy at CERN.



Picture Source : http://te-epc-lpc.web.cern.ch/te-epc-lpc/machines/lhc/pagesources/LHC-Underground-Layout.png.

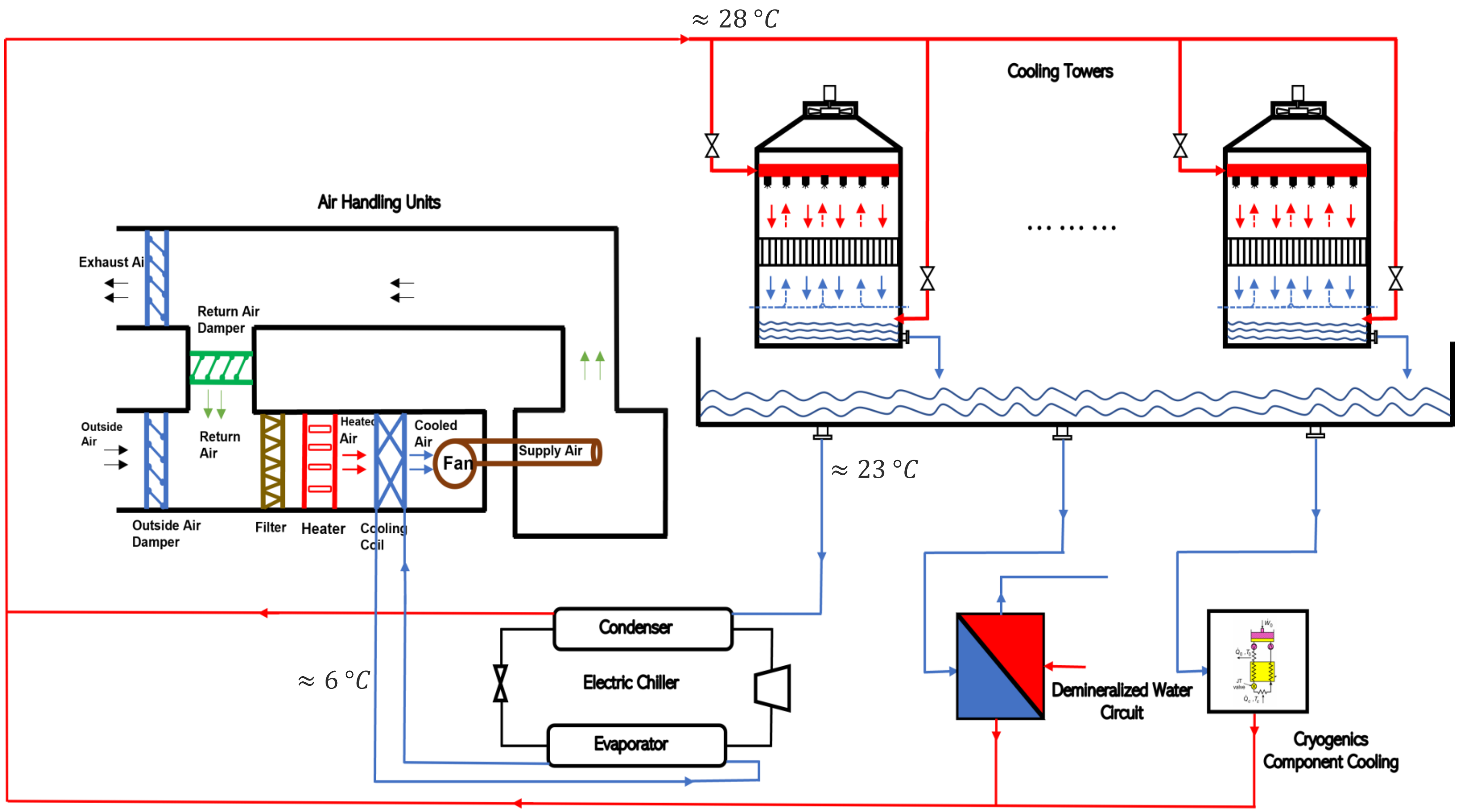
Large Scale Cooling Plant

Main components of a cooling plant include:

- Cooling Towers
- Chillers
- Air Handling Units

Other components:

- Pumps
- Storage Elements



Energy Management in Heating, Ventilation and Cooling Systems

Energy savings in heating, ventilation and cooling systems can be achieved in many different ways.

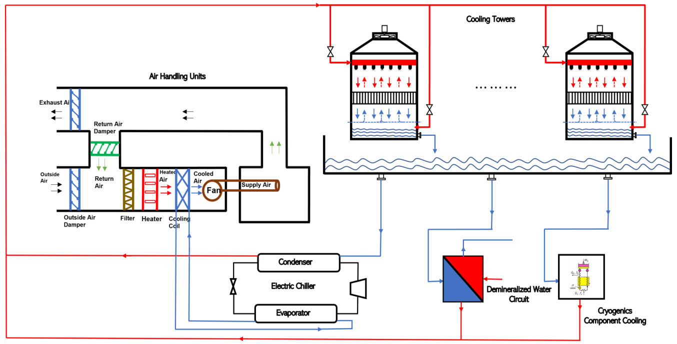
Control Algorithms

Fault detection and diagnosis
Predictive maintenance

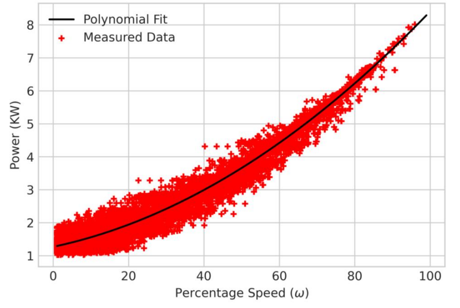
Heating using electrical heater
Heating using heating coil

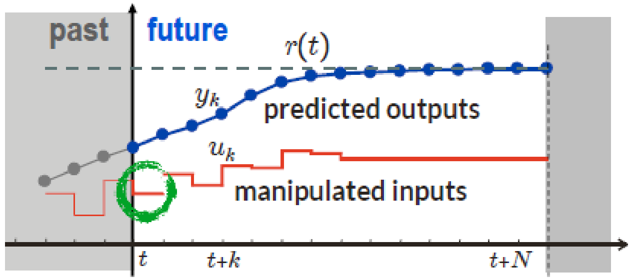
Hot water production using boiler
Hot water production using heat pumps

Cooling Plants at CERN

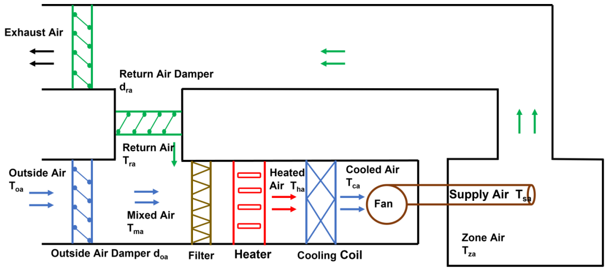


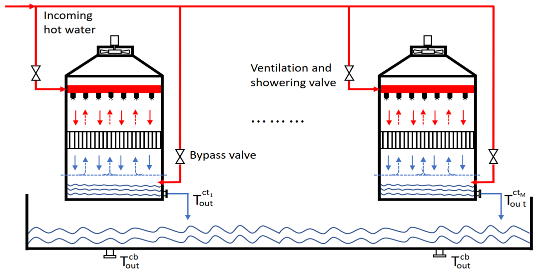
Energy Optimal Control





Case Studies





Control System/Algorithm

Main Operational Goals

AHU : Regulate zone temperature within the desired range (e.g $[18°C\ - 26°C]$).

Cooling Towers : Regulate outlet water temperature to the desired setpoint (e.g $[22°C]$).

Chillers : Produce chilled water at desired temperature (e.g $6°C$)

Control System

Algorithms that deteremine the sequence of actions that acheives the main operational goals of the equipment.

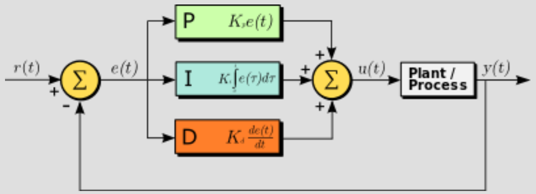
Process Control Landscape

Adaptation of different control methodologies in industry over the years.

Current

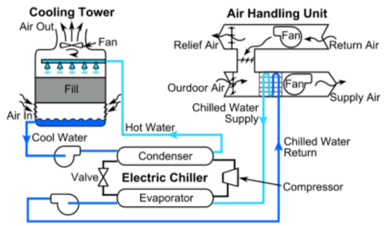
Classical Control

- PID (Cascade, Split Range e.tc)
- Rule Based/Heuristics



Static Optimization

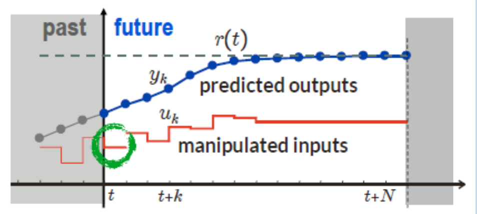
- Plant Wide (Setpoint) Optimization
- Static Process Models



Study Scope

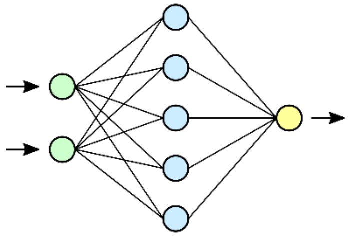
Dynamic Optimization

- Model Predictive Control
- Dynamic Process Models



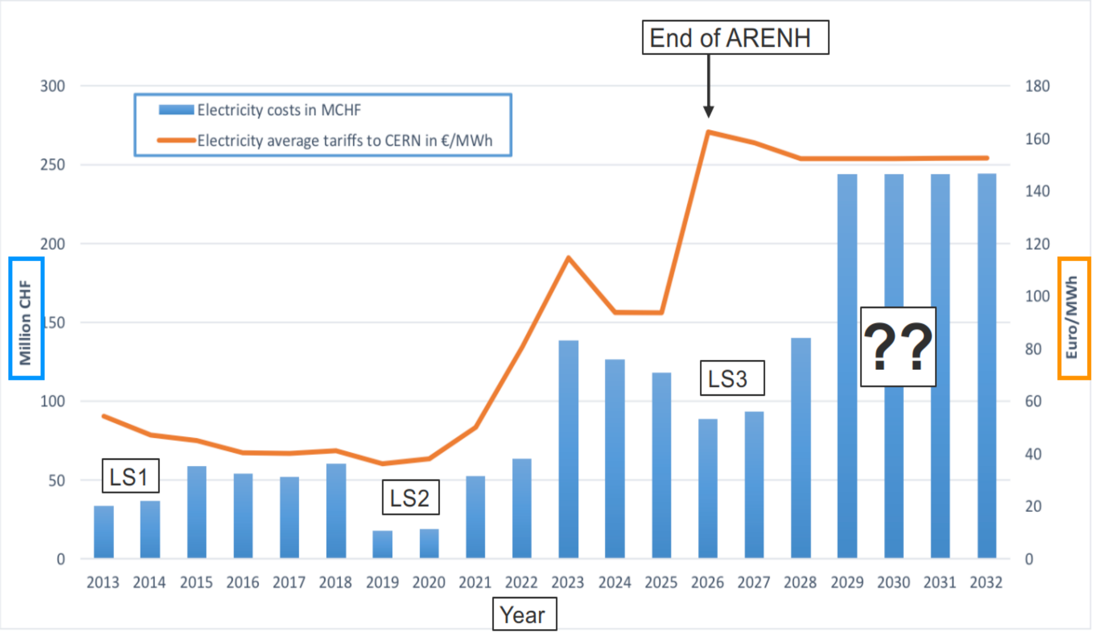
Machine Learning

- Neural Networks
- Reinforcement Learning



Why Energy Optimal Control?

Major escalation of electricity prices in the upcoming years for CERN.



1MWh ≈ 40 € (2022).

1MWh ≈ 160 € (2025).

Control Algorithms ⟶ **Real-time Process Control + Process Economic Optimization.**

Picture Source : September Council Meeting CERN

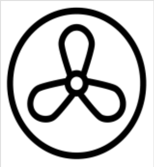
Energy Optimal Control Algorithm

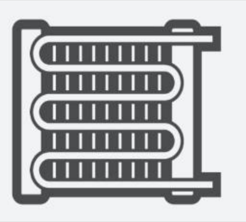
Achieve Control Specifications + Minimum Energy Usage

Model predictive control is one of the most structured way of designing energy optimal controllers.

Step-1

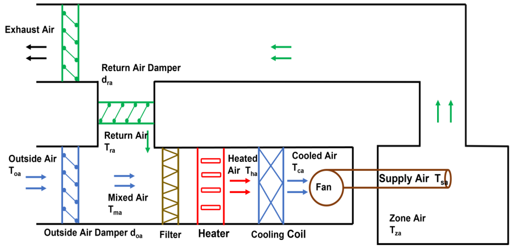
Model Actuators Power Consumption

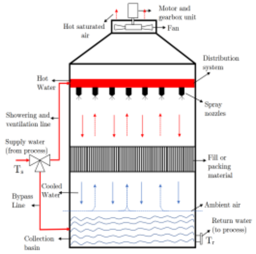




Step-2

Model System Dynamics





Step-3

Solve a Constrained Optimization Program (MPC)

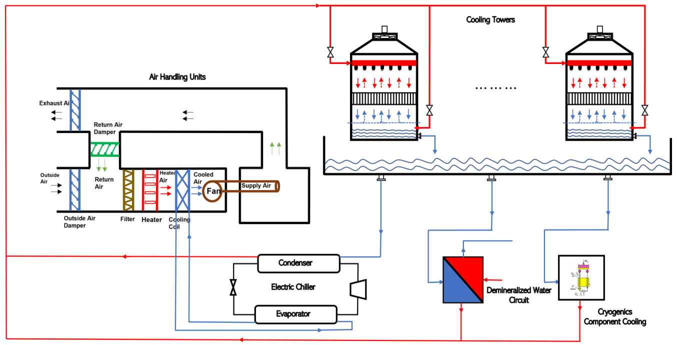
$$\min \sum_{k=0}^{N-1} \|W^y(y_k - r(t))\|_2^2 + \|W^u(u_k - u_r(t))\|_2^2$$

s.t.

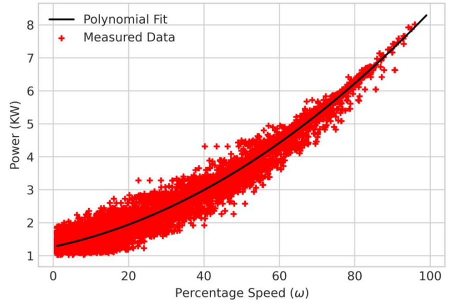
$$x_{k+1} = f(x_k, u_k) \quad \text{prediction model}$$
$$y_k = g(x_k)$$
$$u_{\min} \leq u_k \leq u_{\max} \quad \text{constraints}$$
$$y_{\min} \leq y_k \leq y_{\max}$$
$$x_0 = x(t) \quad \text{state feedback}$$

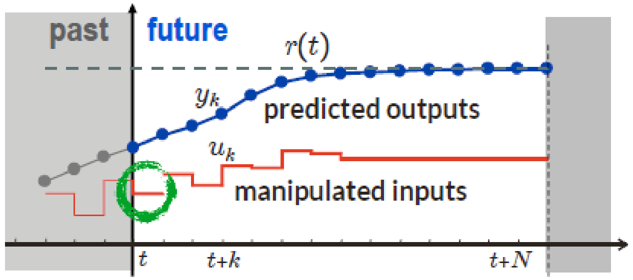
Picture Source (Optimization) : http://cse.lab.imtlucca.it/~bemporad/teaching/mpc/imt/1-linear_mpc.pdf

Cooling Plants at CERN

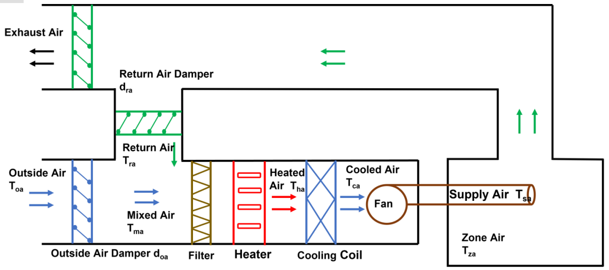


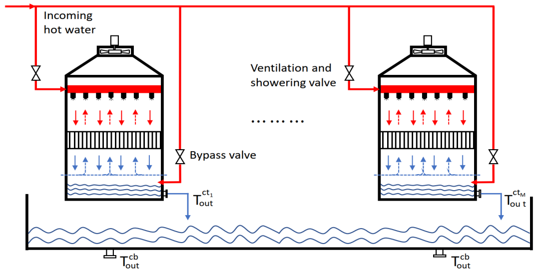
Energy Optimal Control





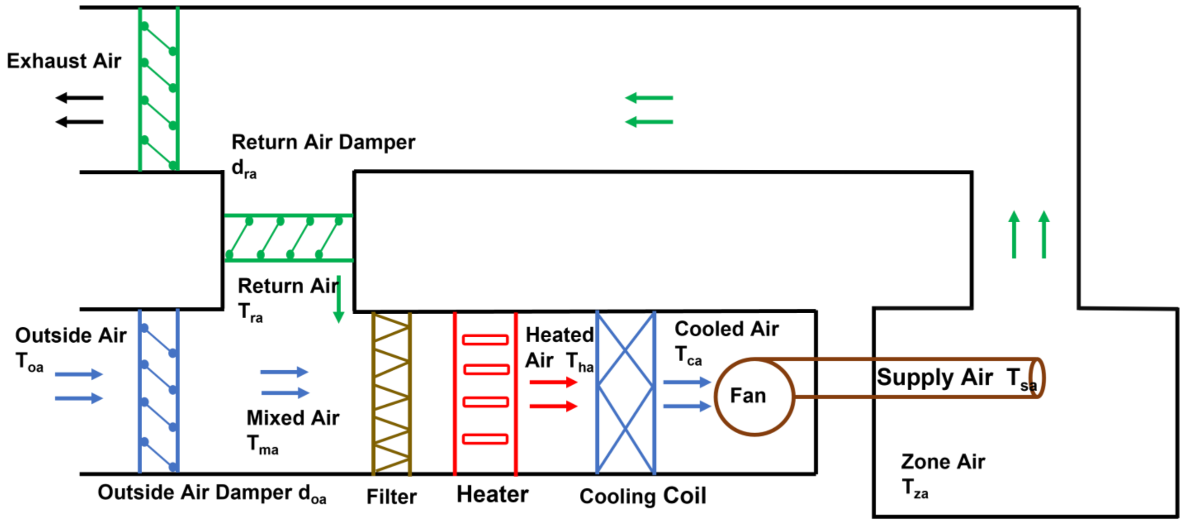
Case Studies





Case Study : Air Handling Unit

Goal: Maintain thermal comfort and indoor air quality of the zone. Temperature 17 $°C$ to 26 $°C$, Humidity 20% to 60%.



Controlled Variable

- Zone Air Temperature

Disturbance Variable

- Outside Air Temperature

Manipulated Variables

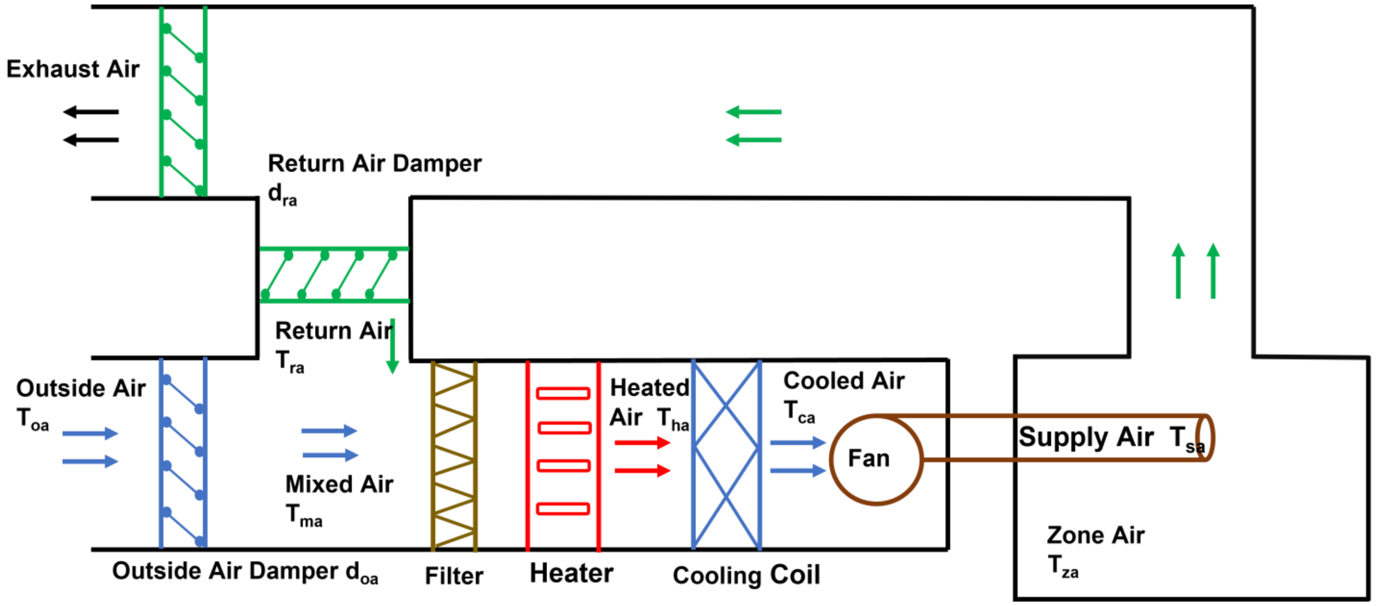
- Outside and Return Air Dampers
- Fan Speed
- Heater/Heating Coil
- Cooling Coil

Case Study : Air Handling Unit

Over-actuated in nature !!!

Depending on weather conditions zone cooling can be acheived using:

- ✓ Fan Only
- ✓ Cooling Coil Only
- ✓ Cooling Coil + Fan

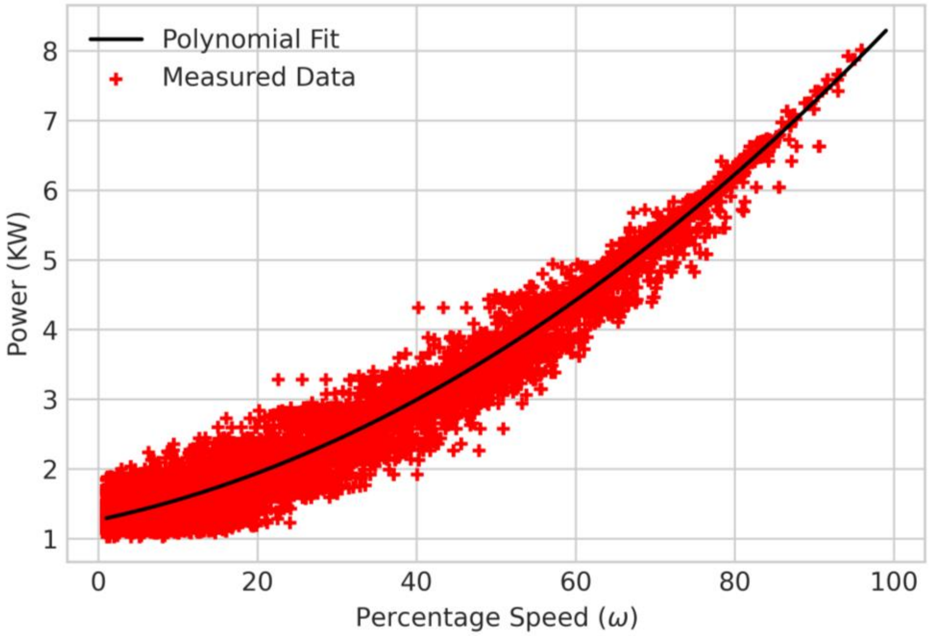


Energy Optimal Control ??

Step-1 : Model Actuator's Power Consumption

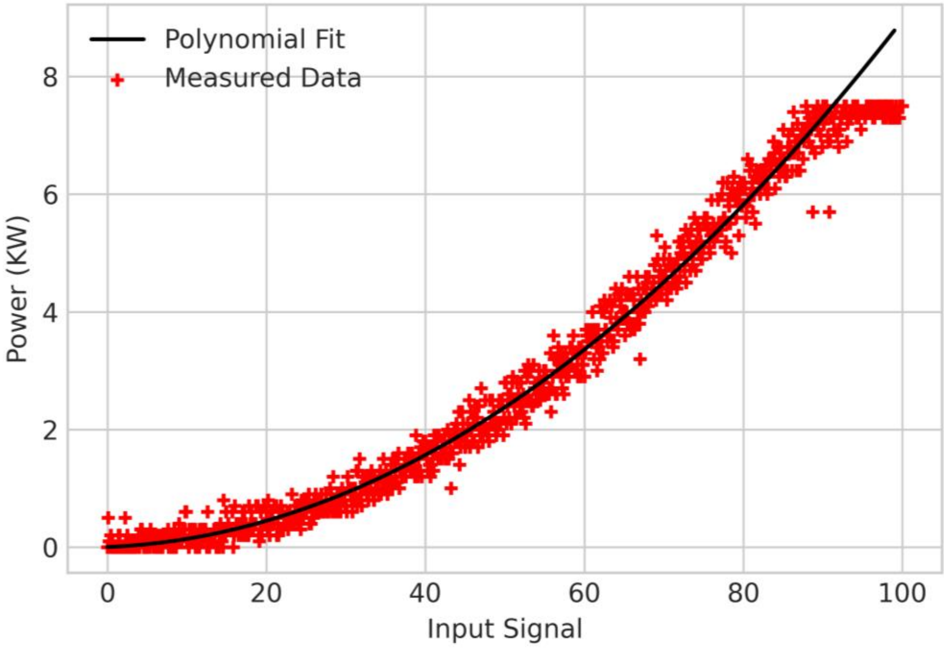
Fan Power Consumption

$$P_{fan} \approx g_0\omega^2 + g_1\omega + g_2$$



Heater Power Consumption

$$P_{heater} \approx f_0\,\gamma^2 + f_1\gamma$$



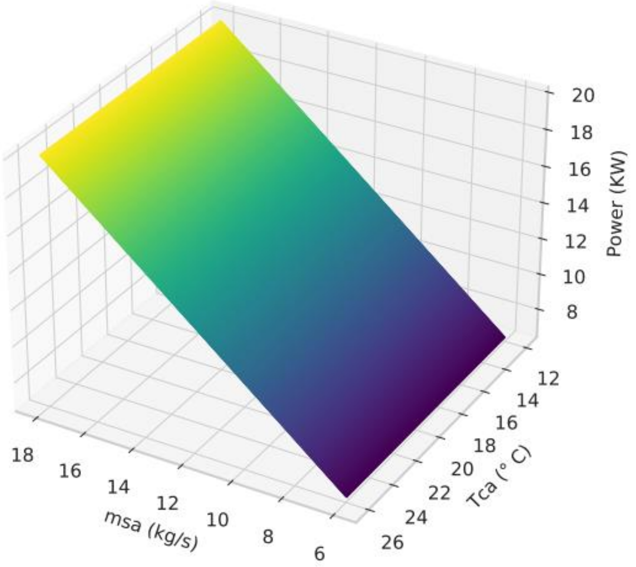
Step-1 : Model Actuator's Power Consumption

Cooling Coil Power Consumption

$$P_{cc} = \frac{m_{sa} C_{pa} (T_{ha} - T_{ca})}{\eta \, COP}$$

Dependence on

- Mass flow rate of air.
- Temperature difference across the coil.
- Efficiency of chilled water production and cooling coil.



Step-2 : Models Different AHU Components

First Principle models based on mass and energy balances

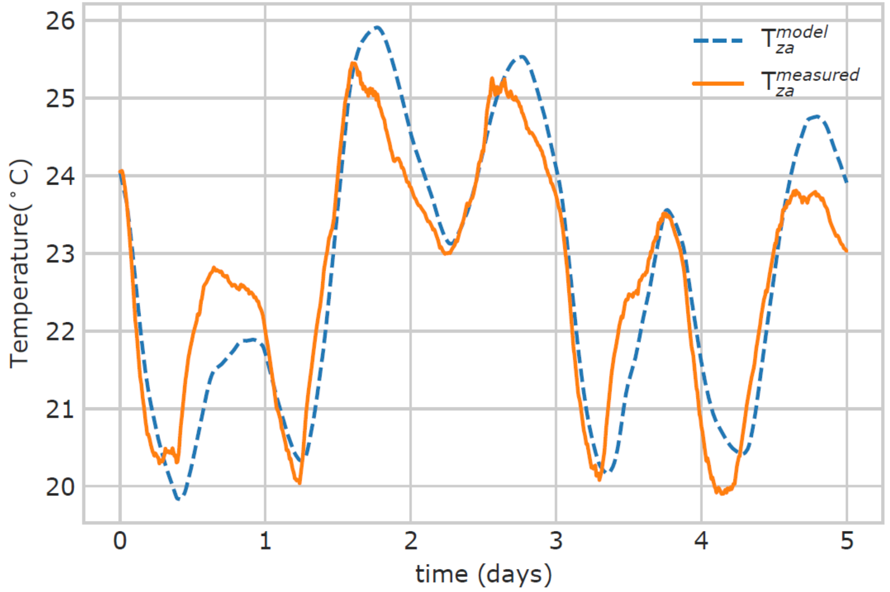
- Dampers
- Mixing Chamber
- Heater
- Zone

Zone Model

$$C_z \frac{dT_{za}}{dt} = m_{sa}C_{pa}T_{sa} - m_{sa}C_{pa}T_{za} + \alpha(T_{oa} - T_{za}) + q(t)$$

Zone temperature depends on

- Mass flow rate and temperature of supply air
- Outside air temperature
- Internal zone load



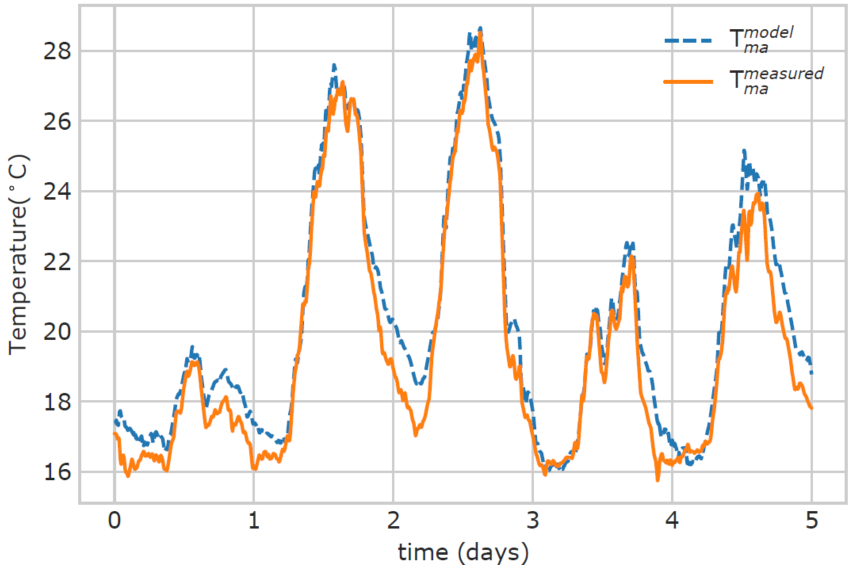
Step-2 : Models for Different AHU Components

Mixing Chamber

$$C_m \frac{dT_{ma}}{dt} = \dot{m}_{oa} C_{pa} T_{oa} + \dot{m}_{ra} C_{pa} T_{ra} - \dot{m}_{sa} C_{pa} T_{ma}$$

Mixing chamber temperature mainly depends on

- Mass flow rate and temperature of outside air
- Mass flow rate and temperature of return air

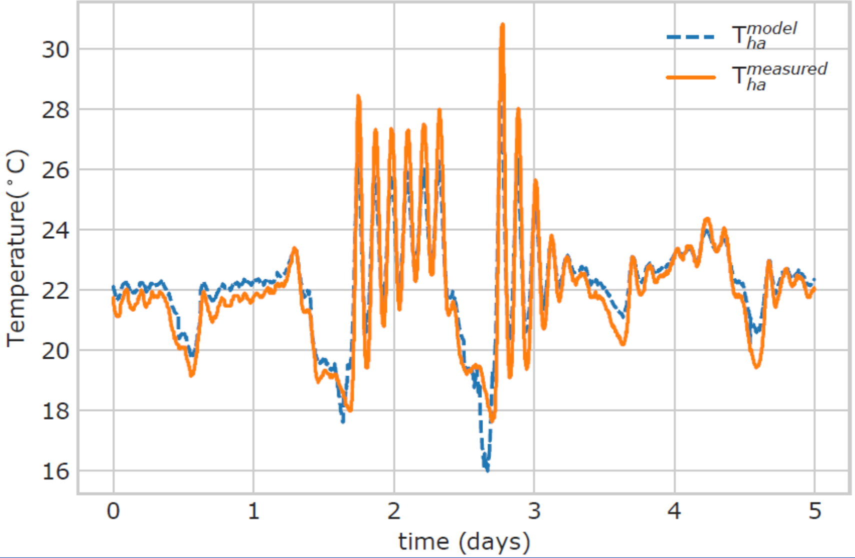


Heater Model

$$C_h \frac{dT_{ha}}{dt} = \dot{m}_{sa}^{in} C_{pa} T_{ma} - \dot{m}_{sa}^{out} C_{pa} T_{ha} + P_h(\gamma)$$

Heated air temperature mainly depends on

- Heater input
- Flow rate of supply air
- Mixed air temperature



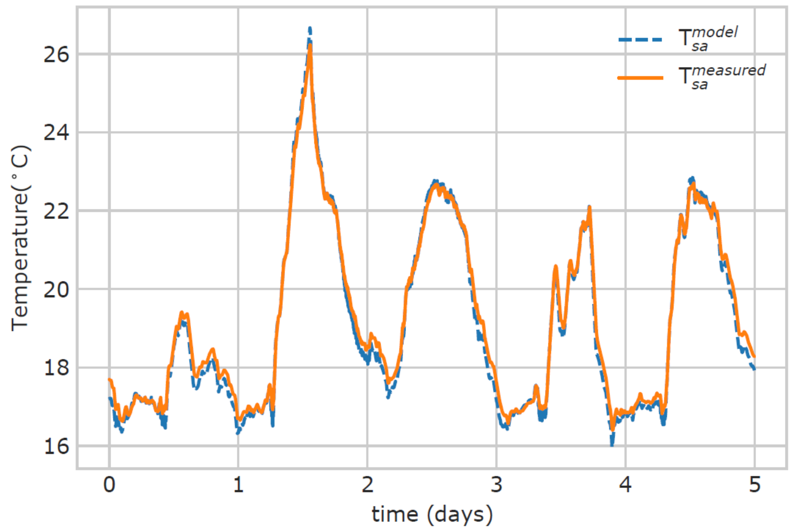
Step-2 : Models for Different AHU Components

Fan thermal gain

$$T_{sa} = T_{ca} + \frac{\beta\, P_f(\omega)}{\dot{m}_{sa} C_{pa}}$$

Fan thermal gain mainly depends on

- Fan Speed
- Flow rate of supply air



More Details

Model Predictive Control of Air Handling Unit for a Single Zone Setup, 7th International Symposium on Advanced Control of Industrial Processes at UBC Vancouver.

Step-3 : Solve an Optimization Program

Define Control Specifications

- Regulate the zone temperature within desired range $[18°C - 26°C]$.
- Fan speed limit constraint $[33\% - 100\%]$.
- Supply air temperature constraints $(17°C - 30°C)$ to avoid condensation and maintain thermal comfort.
- Minimum outside air damper opening constraint (10%) to maintain indoor air quality.
- Physical limits on the rate of change of actuator inputs must be respected.

Utilize Minimum Energy

Step-3 : Solve an Optimization Program

Find best control actions that minimizes the total power consumption over a period of 16 hours.

$$\min_{\mathbf{d},\boldsymbol{\omega},\boldsymbol{\gamma},\boldsymbol{\epsilon},\mathbf{T}} \sum_{k=0}^{N} P_f(\omega[k]) + P_h(\gamma[k]) + P_c(T_{ca}[k{+}1]) + \mathbf{r}^T \boldsymbol{\epsilon}^2$$

⟵ Minimize total power consumption

$$\begin{aligned}
\text{s.t}\quad & T_{za}[k{+}1] = f_{za}(T_{za}[k], T_{sa}[k], T_{oa}[k], \omega[k]), \forall k \in \mathcal{K}_N \\
& T_{ma}[k{+}1] = f_{ma}(T_{za}[k], T_{oa}[k], d_{oa}[k]), \forall k \in \mathcal{K}_N \\
& T_{ha}[k{+}1] = f_{ha}(T_{ma}[k], \gamma[k]),\ \forall k \in \mathcal{K}_N \\
& T_{ca}^{min} \leq T_{ca}[k{+}1] \leq T_{ha}[k{+}1],\ \forall k \in \mathcal{K}_N \\
& T_{sa}[k{+}1] = f_{fan}(T_{ca}[k]),\ \forall k \in \mathcal{K}_N
\end{aligned}$$

⟵ Dynamics of different AHU components

$$\begin{aligned}
& T_{sa}^{min} - \epsilon_{sa} \leq T_{sa}[k{+}1] \leq T_{sa}^{max} + \epsilon_{sa},\ \forall k \in \mathcal{K}_N \\
& T_{za}^{min} - \epsilon_{za} \leq T_{za}[k{+}1] \leq T_{za}^{max} + \epsilon_{za}, \forall k \in \mathcal{K}_N \\
& d_{oa}^{min} \leq d_{oa}[k] \leq d_{oa}^{max},\ \forall k \in \mathcal{K}_N \\
& \omega^{min} \leq \omega[k] \leq \omega^{max},\ \forall k \in \mathcal{K}_N \\
& \gamma^{min} \leq \gamma[k] \leq \gamma^{max},\ \forall k \in \mathcal{K}_N
\end{aligned}$$

⟵ Maximum and Minimum allowed values of different variables.

$$\begin{aligned}
& -\dot{d}_{oa} \leq d_{oa}[k{+}1] - d_{oa}[k] \leq \dot{d}_{oa},\ \forall k \in \mathcal{K}_N \\
& -\dot{\omega} \leq \omega[k{+}1] - \omega[k] \leq \dot{\omega},\ \forall k \in \mathcal{K}_N \\
& -\dot{\gamma} \leq \gamma[k{+}1] - \gamma[k] \leq \dot{\gamma},\ \forall k \in \mathcal{K}_N \\
& -\dot{T}_{ca} \leq T_{ca}[k{+}1] - T_{ca}[k] \leq \dot{T}_{ca},\ \forall k \in \mathcal{K}_N
\end{aligned}$$

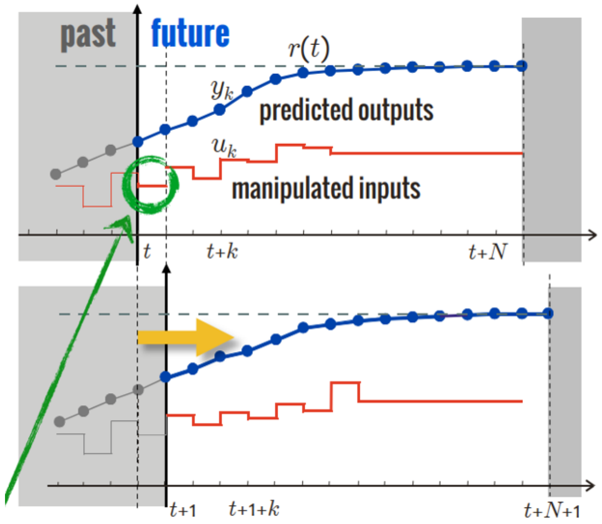
⟵ Physical Limits on the rate of change constraint

Output: Dampers Opening, Fan Speed, Heater Input, Cooled Air Temperature

Step-3 : Solve an Optimization Program

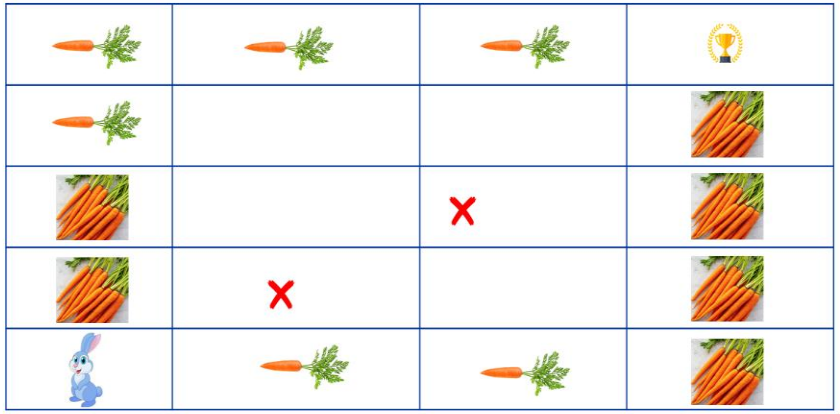
Resolve the optimization program at each sampling instant

To overcome disturbances and model mismatch.



Why optimize over a prediction horizon of 16-hours ?

Future information can be critical in taking the right control action at the present time step.

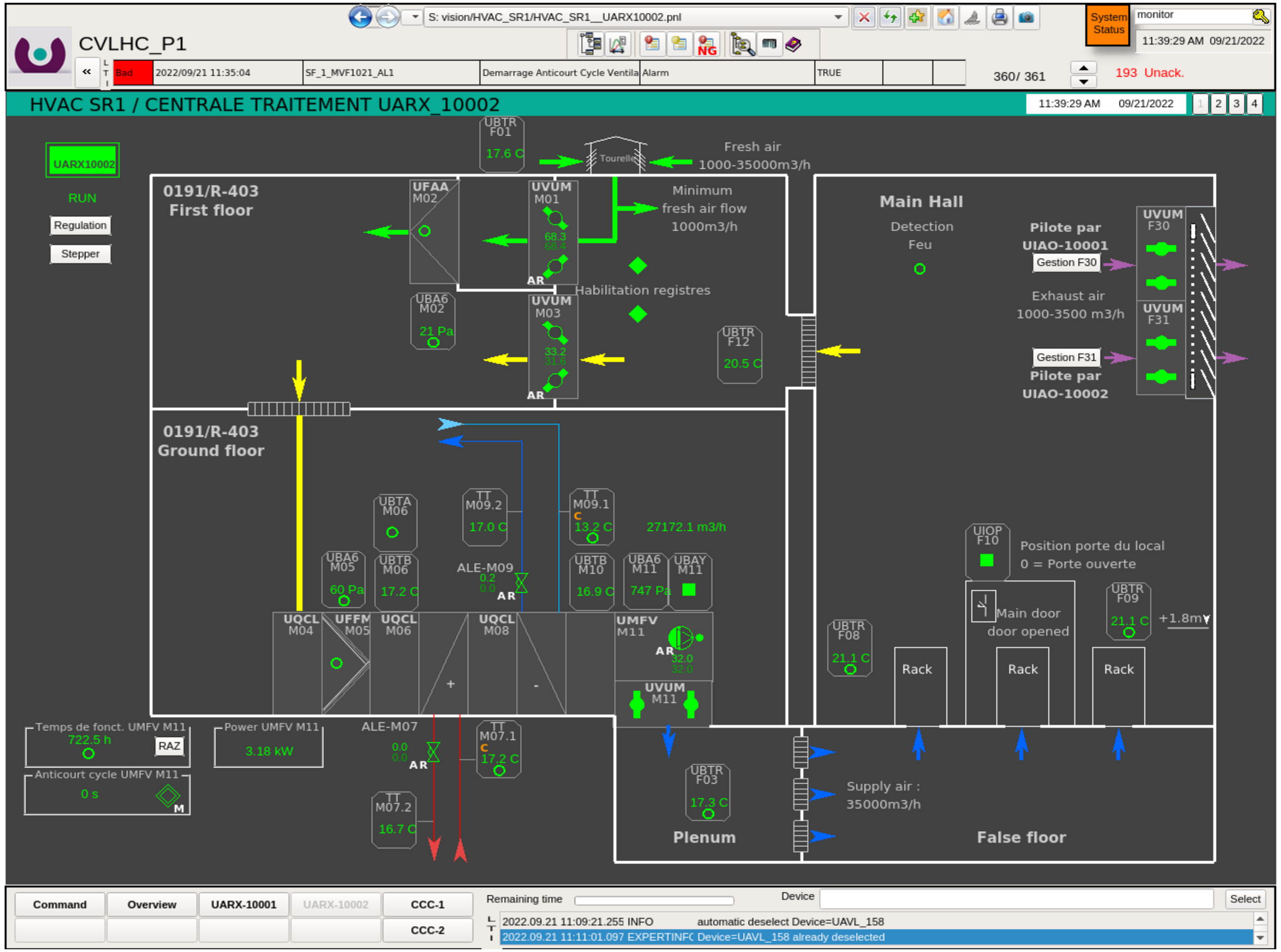


Results : Evaluation Procedure

High Fidelity model of SR-1 HVAC in Ecosim developed for virtual commissioning applications.

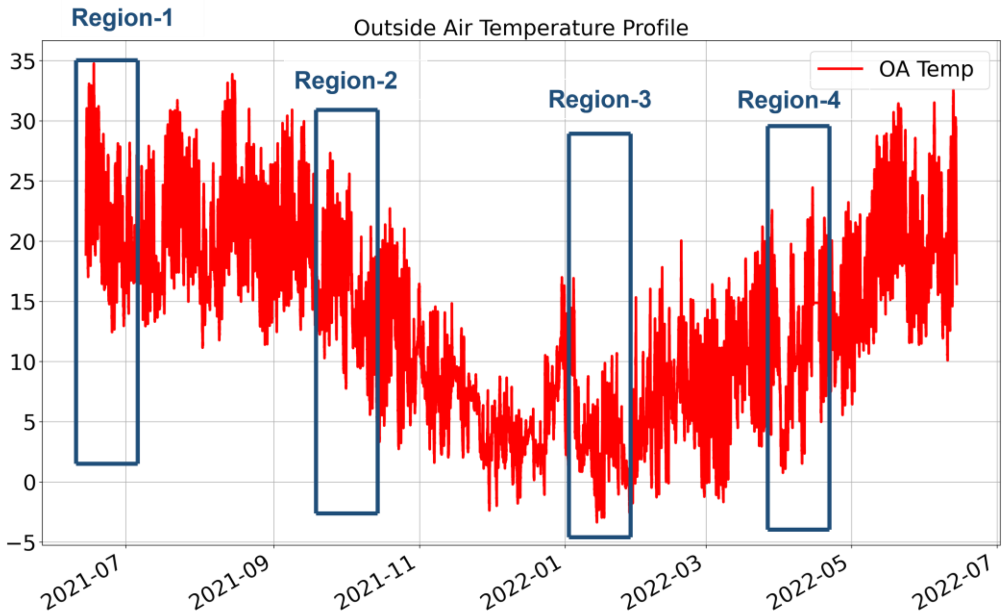
Key Features:

- Motorized Dampers
- VFD Driven Fan
- Cooling Coil
- Heating Coil
- Less Critical
- Well Instrumented



Results : Energy Consumption Comparison

2021-06-11 to 2022-06-30



Estimated Energy Savings (Pilot Plant)

	Region	MPC (KWh)	Cascade (KWh)	% Saving
Region-1	Summer	3178	4008	20.7 %
Region-2	Summer - Winter	1185	1557	23.9%
Region-4	Winter-Summer	942	1064	11.4%

30 days in each region.

Potential Savings (≈ 200 AHU)

HVAC Electricity Consumption ≈ 30GWh/year
15% Reduction
4.5GWh/Year, 600kCHF

Courtesy: EN-CV-CL

EN-CV-CL : https://indico.cern.ch/event/1217431/

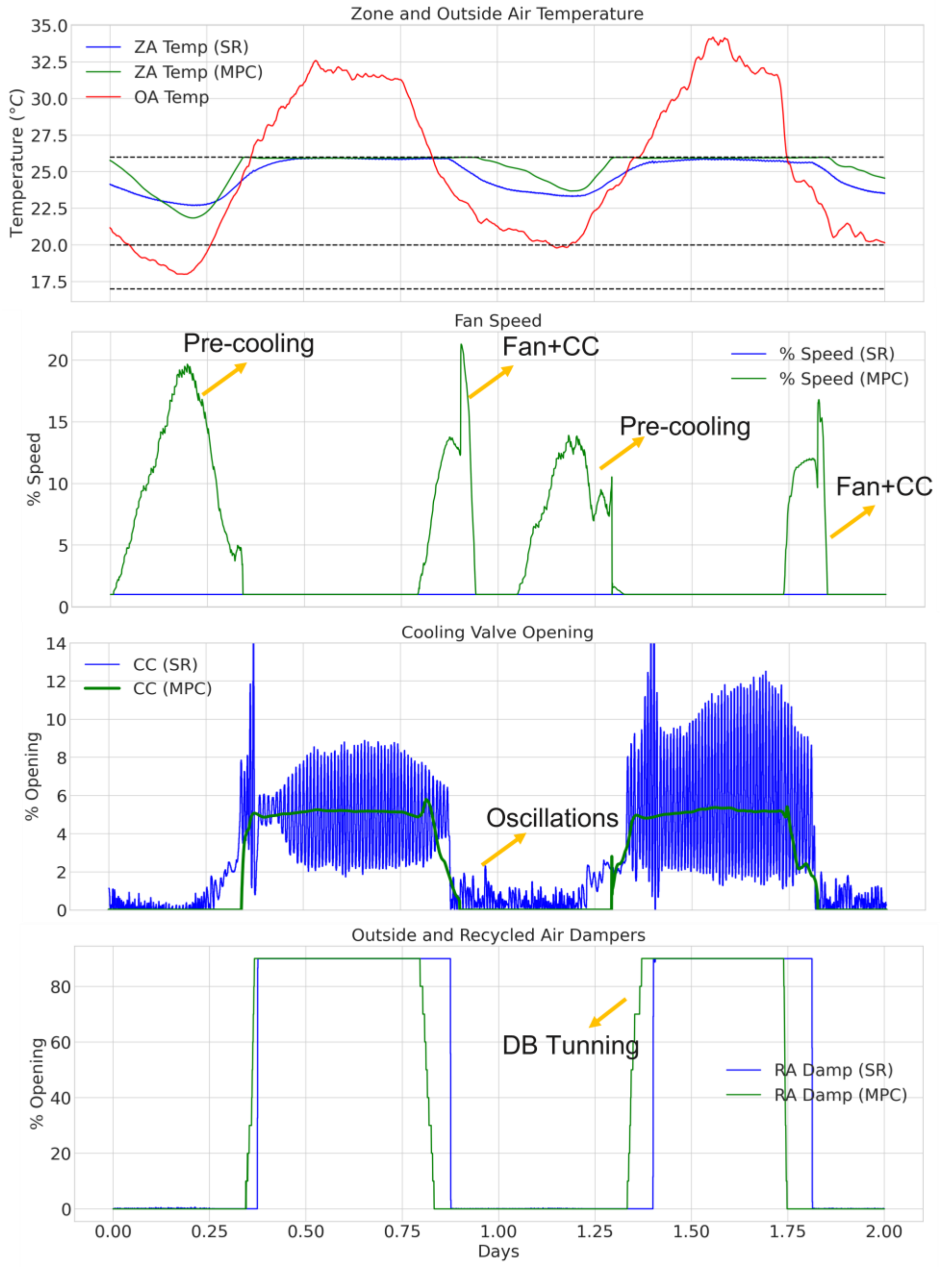
Results : Performance Comparison

Oscillations : Oscillations can decrease the life-time of the equipment.

Pre-cooling : Precool the zone in the region of low outside air temperature to completely or partially avoid the cooling in the upcoming regions of high outside air temperature.

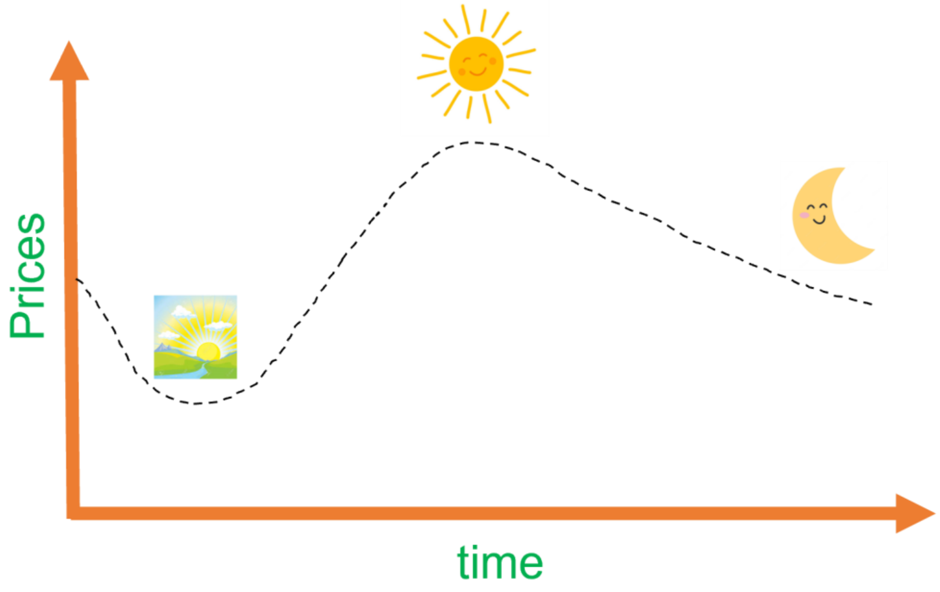
Efficient Actuators Usage : Fan + Cooling Coil.

Dampers Dead Band : In MPC rate of change constraints can ensure smooth opening/closing of dampers.



Results : Future Needs

Dynamic Energy Prices



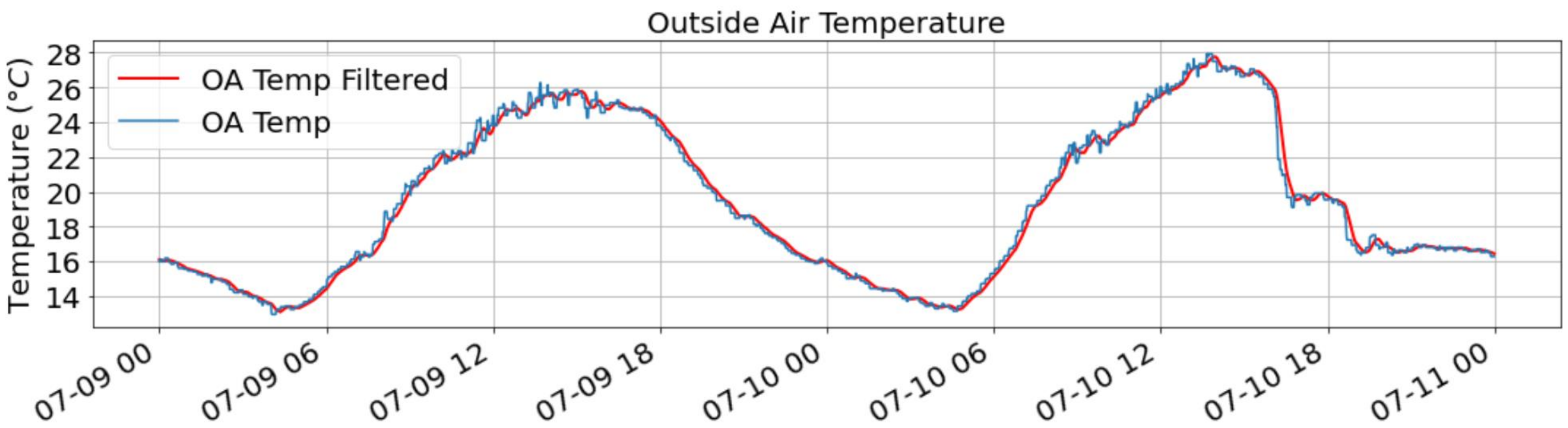
- Peak Load Reduction: Evenly distribute the load throughout the day.
- Renewable Energy Integration: Cheaper electricity can be offered in the regions of low energy usage.

No Feedback controller can be energy optimal.

Results : Noise and Real Time Model Adaptation

Noise

Good filters must be designed.



Real Time Model Adaptation

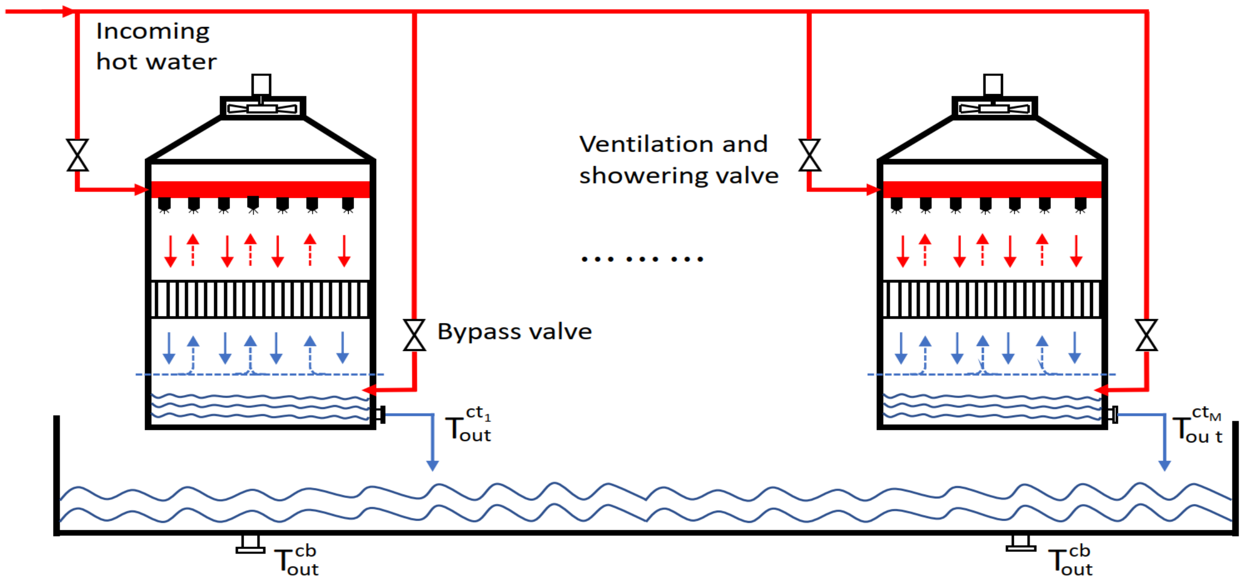
Operating conditions can change.

$$C_z \frac{dT_{za}}{dt} = m_{sa} C_{pa} T_{sa} - m_{sa} C_{pa} T_{za} + \alpha (T_{oa} - T_{za}) + q(t)$$

Kalman Filter
Moving Horizon Estimation

Case Study : Cooling Towers

Goal : Regulate the outlet water temperature of the common basin to a desired setpoint.



Operational Modes :

- Ventilation ⟶ Speed modulation (Minimum speed ≈ 60% of the rated speed)
- Showering Mode ⟶ Free cooling
- Bypass Mode ⟶ Incoming water goes into collection basin.

Simultaneously determine the best operational mode and optimal fan speed !!

Case Study : Cooling Towers

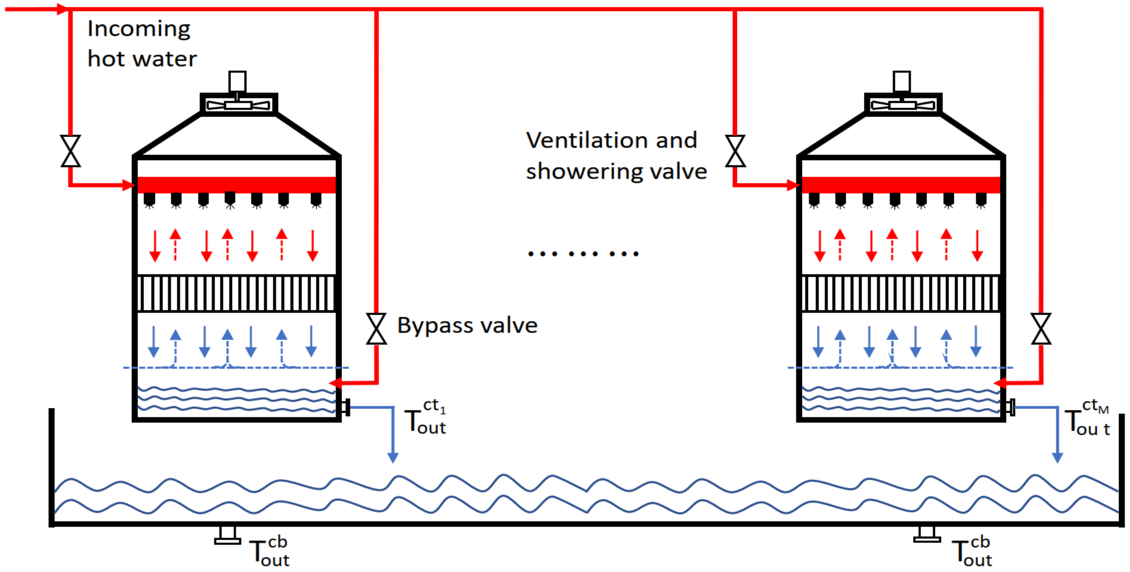
Over-actuated in nature !!!

Different configurations can acheive the same goal (e.g provide same heat rejection capacity).

✓ Run 2 Fans

Fan-1 Speed = 100%

Fan-2 Speed = 100%



✓ Run 3 Fans

Fan-1 Speed = 75%

Fan-2 Speed = 75%

Fan-3 Speed = 75%

Energy Optimal Control ??

Step1,2 : Model Actuator Power and System Dynamics

Fan Power Consumption

$$P_{fan} \approx \alpha_0 \omega^2 + \alpha_1 \omega + \alpha_2$$

Ventilation Mode (Forced Draft)

$$\frac{dT_{out}}{dt} = -c_1 \dot{m}_w [T_{out} - T_s] - c_2 \dot{m}_w^l [\frac{\dot{m}_a^l}{\dot{m}_a^l + c_3 \dot{m}_w^l}][T_s - T_{wb}^i]$$

Outlet water temperature of the common basin depends on

- Temperature and mass flow rate of the incoming hot water.
- Wet bulb temperature and mass flow rate of the ambient air.

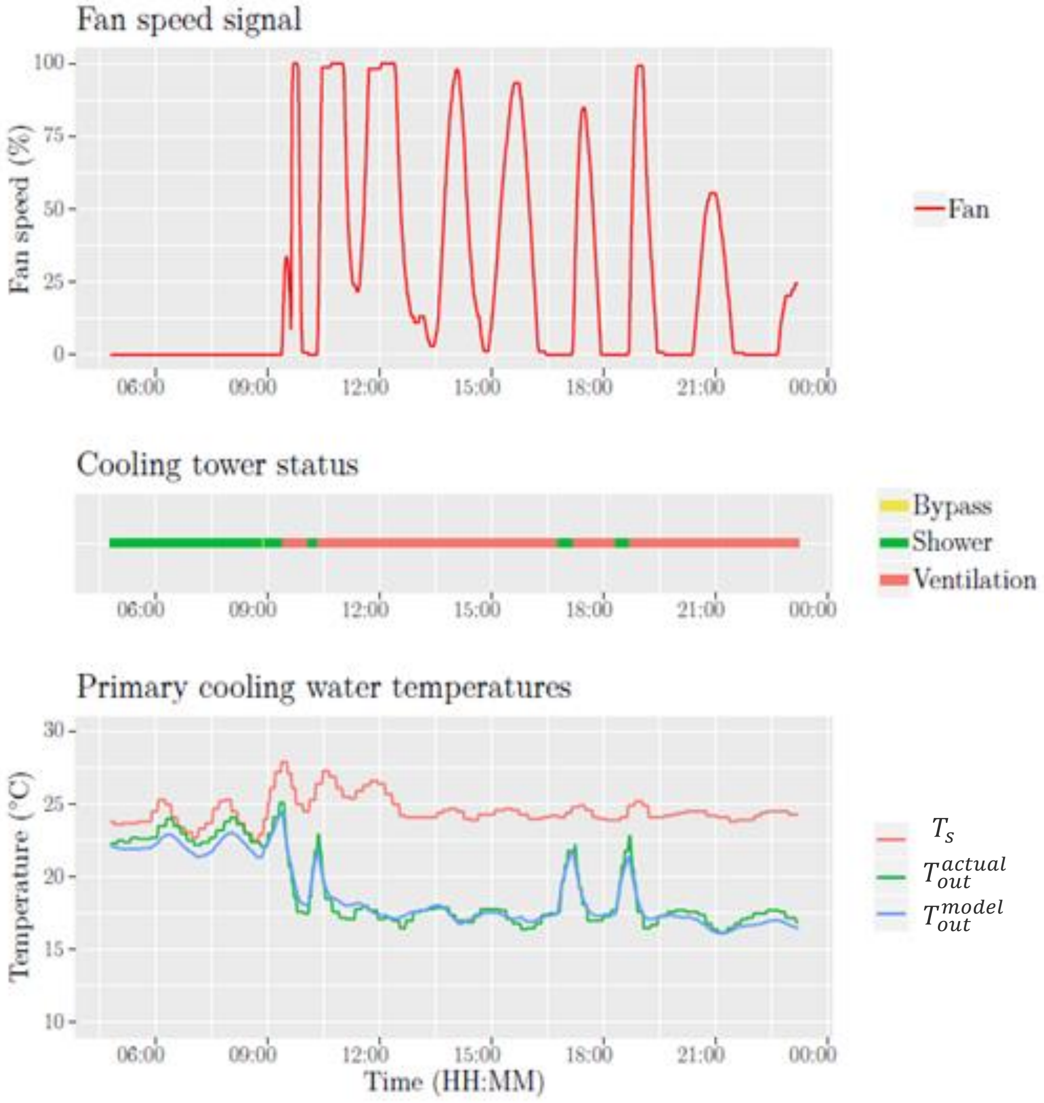
Showering Mode (Natural Draft)

$$\frac{dT_{out}}{dt} = -c_1 \dot{m}_w [T_{out} - T_s] - c_2 \dot{m}_w^l [\frac{\dot{m}_a^l}{\dot{m}_a^l + c_3 \dot{m}_w^l}][T_s - T_{wb}^i]$$

Mass flow rate of the air is roughly fixed.

Bypass Mode

$$\frac{dT_{out}}{dt} = \frac{1}{m}[\dot{m}_w T_s - \dot{m}_w T_{out}]$$



Source : B. Schofield, et al., “Waste heat recovery for lhc cooling towers, control system validation using digital twins”

Step-3 : Solve an Optimization Program

Define Control Specifications

- Regulate outlet water temperature of the common temperature basin.
- Handle physical and operational constraints (e.g minimum fan speed must be 60% of the rated fan speed).
- Take into account different operational efficiencies.
- Avoid excessive switching (e.g allow only one mode switch in 10 minutes).
- Balance run time among identical cooling towers.
- Avoid temperature gradient in the common water collection basin.
- Resilience to actuator failure.

Utilize Minimum Energy

Step-3 : Solve an Optimization Program

Find the best operational mode and optimal fan speed that minimizes the total power consumption

$$J = \sum_{j=1}^{M} \sum_{k=1}^{N} r^j P^j(u^j[k])$$

← Minimize total power consumption of cooling towers

$$(1 - b_v^{ct_j}[k]) m_1^{ct_j} \leq T_{out}^{ct_j}[k+1] - f_{vent}^{ct_j}(T_{out}^{ct_j}[k], u^j[k]) \leq (1 - b_v^{ct_j}[k]) M_1^{ct_j}, \forall k \in \mathcal{K}, \forall j \in \mathcal{C}$$

$$(1 - b_s^{ct_j}[k]) m_2^{ct_j} \leq T_{out}^{ct_j}[k+1] - f_{show}^{ct_j}(T_{out}^{ct_j}[k]) \leq (1 - b_s^{ct_j}[k]) M_2^{ct_j}, \forall k \in \mathcal{K}, \forall j \in \mathcal{C}$$

$$(1 - b_b^{ct_j}[k]) m_3^{ct_j} \leq T_{out}^{ct_j}[k+1] - f_{byp}^{ct_j}(T_{out}^{ct_j}[k]) \leq (1 - b_b^{ct_j}[k]) M_3^{ct_j}, \forall k \in \mathcal{K}, \forall j \in \mathcal{C}$$

$$b_v^{ct_j}[k] + b_s^{ct_j}[k] + b_b^{ct_j}[k] = 1, \forall k \in \mathcal{K}, \forall j \in \mathcal{C}$$

← Handling operational modes

$$b_v^{ct_j}[k] u_{min}^{ct_j} \leq u^{ct_j}[k] \leq b_v^{ct_j}[k] u_{max}^{ct_j}, \forall k \in \mathcal{K}, \forall j \in \mathcal{C}$$

← Minimum speed requirement

$$T_{min}^{cb} - \epsilon^{cb} \leq T_{out}^{cb}[k] \leq T_{max}^{cb} + \epsilon^{cb}, \forall k \in \{2, \cdots N+1\}$$

← Regulate outlet water temperature

$$T_{min}^{ct_j} - \epsilon^{ct_j} \leq T_{out}^{ct_j}[k] \leq T_{max}^{ct_j} + \epsilon^{ct_j}, \forall k \in \{2, \cdots N+1\}$$

← Avoid temperature gradient in CB

$$b_v^{ct_j}[i] \geq b_v^{ct_j}[k] - b_v^{ct_j}[k-1], \forall i \in \{k, \ldots, \min(N, k + up_v)\}$$

$$b_s^{ct_j}[i] \geq b_s^{ct_j}[k] - b_s^{ct_j}[k-1], \forall i \in \{k, \ldots, \min(N, k + up_s)\}$$

$$b_s^{ct_j}[i] \geq b_s^{ct_j}[k] - b_s^{ct_j}[k-1], \forall i \in \{k, \ldots, \min(N, k + up_b)\}$$

$$\forall k \in \{U^{ct_j} + 1, \cdots, N\}, \forall j \in \mathcal{C}$$

← Avoid excessive switching

$$b_v^{ct_j}[k] \leq (1 - \lambda_v^{ct_j}), \forall k \in \mathcal{K}, \quad \forall j \in \mathcal{C}$$

$$b_s^{ct_j}[k] \leq (1 - \lambda_s^{ct_j}), \forall k \in \mathcal{K}, \quad \forall j \in \mathcal{C}$$

← Resilience to actuator failure

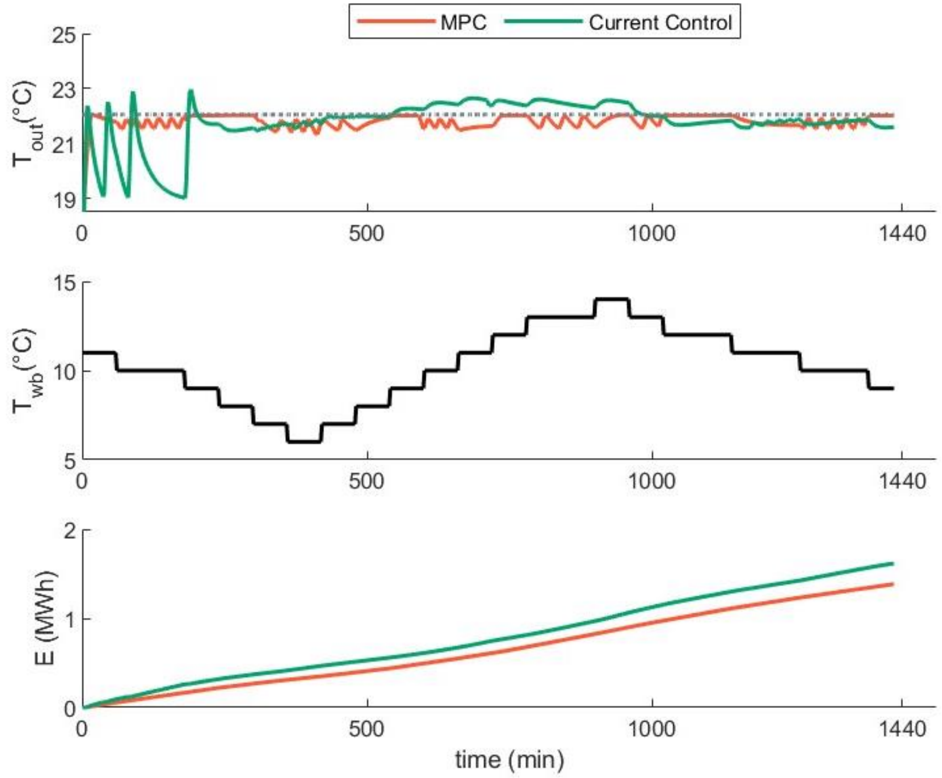
Results : Energy and Performance Comparison

Simulation campaign would be run in different weather conditions in the near future.

	Energy (KWh)	RMSE	Max	% Saving
Legacy Control	2544.4	0.62374	24.733	-
Current Control	1631	0.89476	22.979	-
MPC	1398.9	0.36161	22.053	45.05%, 14.23%

Regulation : Better regulation can be provided.

Excessive switching : Equipment degradation can be avoided.



Total Savings with Current Controller (≈ 25 CTs)

3GWh/Year, 400kCHF

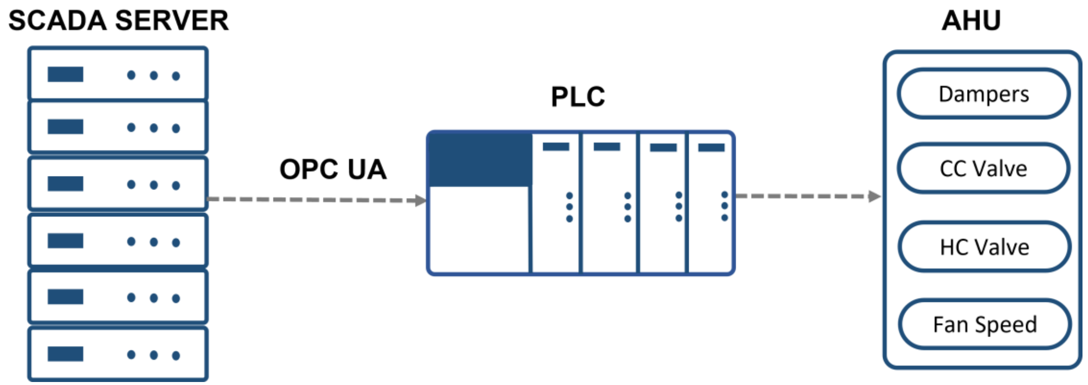
Courtesy: EN-CV-CL

EN-CV-CL : https://indico.cern.ch/event/1217431/

Ongoing Work : Testing Phase

Deployment on the Server (Pilot Implementation)

MPC can be implemented using the currently available industrial infrastructure.



Siemens NanoBox or S7-1500

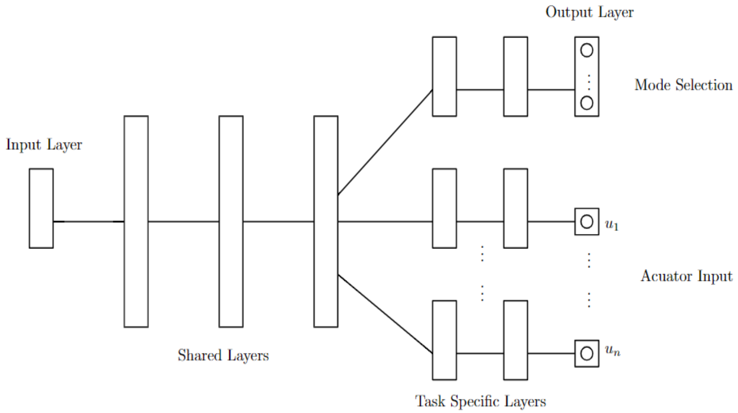
More robust implementation using Siemens NanoBox (Open Lab Project) or Seimens S7-1500.

Picture Source : https://new.siemens.com/

Future Work : Leveraging Deep Learning and Reinforcement Learning

Approximate the solution of Model Predictive Control using a Neural Network

Control law endowed with the properties of model predictive control.



Major Advantage : Can be implemented on a conventional PLC[1] ✓

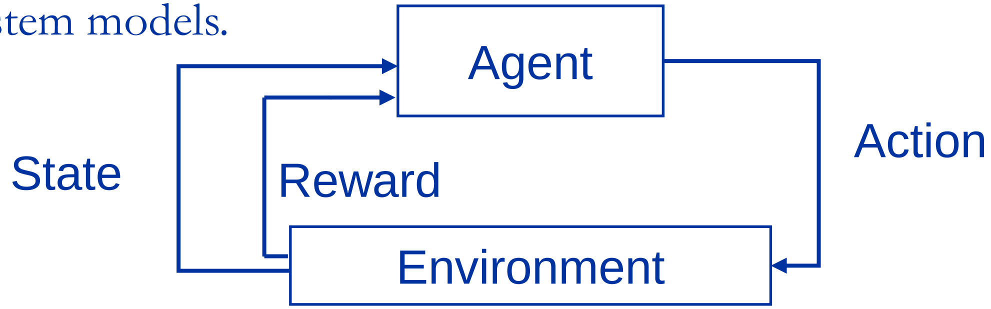
Safety : Does the learned controller satisfy the constraint ? ✓

Stability : Where does the system converges under the influence of the learned controller ?

Adaptability : Operators can change the setpoints/constraints in real time.

Reinforcement Learning

Less dependency on the system models.



Upcoming collaboration with University of Valladolid to benchmark such techniques.

Remark : Depends on the size of the neural networks.

Future Work : Plant Wide (Setpoint) Optimization

Setpoints selection are selected based on the experience

Power consumption of cooling tower, chillers and air handling units are coupled.

Air Side Loop Balance Points

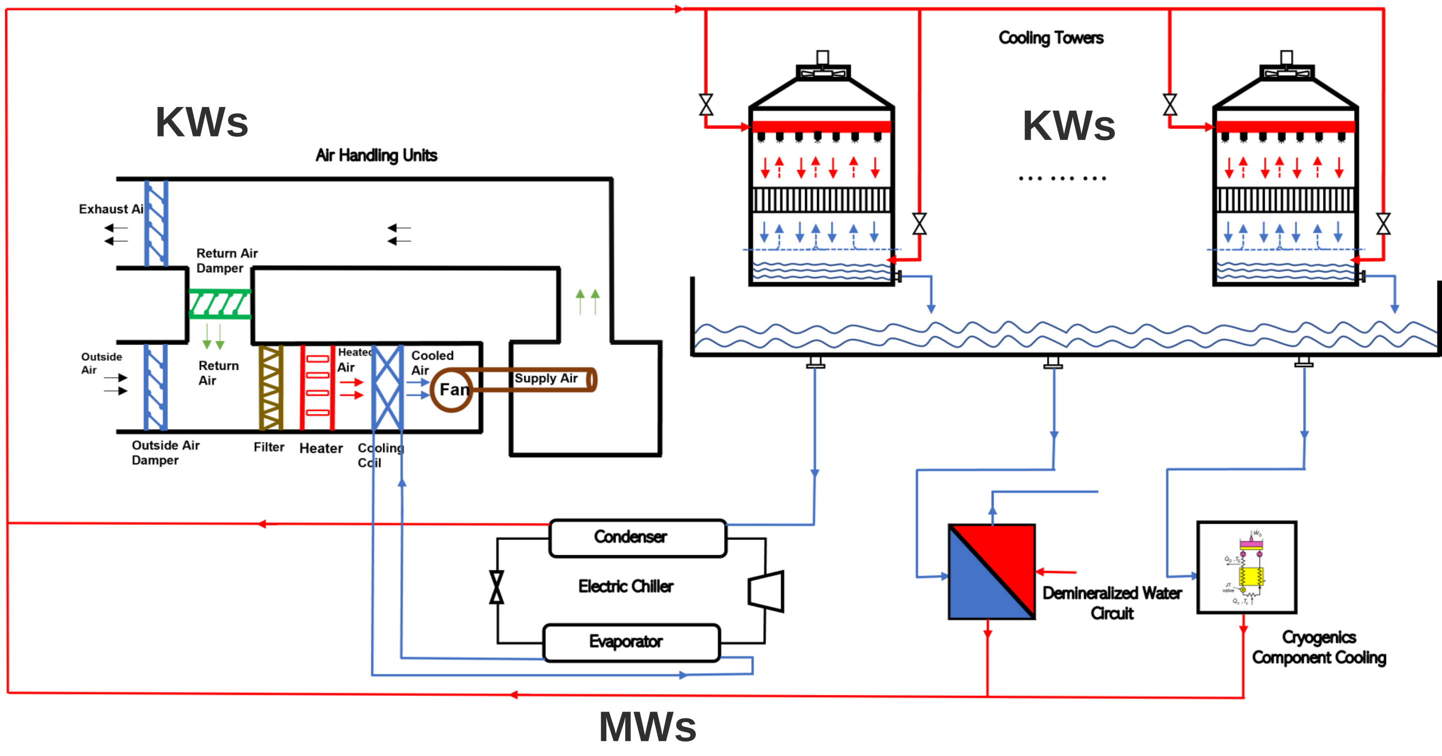
Knobs: 1) Chilled water temperature

2) Pump speed

Water Side Loop Balance Points

Knobs: 1) Condenser water supply temperature

2) Pump speed



Major Energy Saving Potential

Conclusion

MPC can offer

Energy Optimality : Lower bound on the energy consumption.

Performance : Handle complex non-linear interactions in MIMO systems.

Safety : Explicitly handle physical and operational constraint.

Main Philosophy

Better Software : Do better with what's available.

Climate Impact

Byproduct: Reduction in carbon footprint.

Crude Classification

	Process Model	Optimization Program	Computation Complexity	Solver Availability (Open Source)
Linear MPC	Linear Model	Quadratic Program	Low	✓
Non-Linear MPC	Non-Linear Model	Non-linear Program	Intermediate	✓
Hybrid MPC	Continous and Discrete Dynamics	Mixed Integer Program	High	✓

Collaboration and Further Reading

Collaboration

Special thanks to **Cooling and Ventilation Group** (EN-CV) for their close cooperation.

EN

Further Reading

https://www.researchgate.net/project/Energy-Optimal-Control-of-Heating-Ventilation-and-Cooling-Systems

Model Predictive Control of Air Handling Unit for a Single Zone Setup
Preprint   Full-text available · Jun 2022
Faiq Ghawash · Morten Hovd · Brad Schofield · Diogo Monteiro
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Model Predictive Control of Induced Draft Cooling Towers in a Large Scale Cooling Plant
Preprint   Full-text available · Apr 2022
Faiq Ghawash · Morten Hovd · Brad Schofield
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Optimal Control of Induced Draft Cooling Tower using Mixed Integer Programming
Conference Paper   Full-text available · Aug 2021
Faiq Ghawash · Morten Hovd · Brad Schofield
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Capacity Control of Induced Draft Cooling Tower using Two Stage Optimization
Conference Paper   Full-text available · Oct 2021
Faiq Ghawash · Morten Hovd · Brad Schofield
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Questions