

Energy Consumption Optimisation using Advanced Control Algorithms

Brad Schofield, Faiq Ghawash and Enrique Blanco

[Introduction](#page-3-0)

[Pilot Project: Air Handling Units \(AHU\)](#page-6-0)

[Model Predictive Control \(MPC\)](#page-9-0)

[Implementation](#page-19-0)

[Virtual Commissioning](#page-21-0)

[Results](#page-23-0)

[Conclusions](#page-29-0)

Introduction

CERN's energy consumption is high (1.3 TWh per year), and costs are rising

October 5, 2023 [Advanced Control for Energy Optimization](#page-0-0) 4

Energy Efficient Operation

- Energy per luminosity delivered (GWh/fb-1)
- Expected energy per luminosity delivered (GWh/fb·1)
- LHC energy consumption (GWh)
- Expected LHC energy consumption (GWh) O
- Focus on energy consumed per luminosity delivered GWh/fb^{-1}
- Running accelerators less saves money, but doesn't help this metric
- Need to be able to reduce consumption while continuing to operate as normal
- Improved controls for infrastructure can help!

Cooling and Ventilation

Cooling and ventilation at CERN consumes considerable energy (66 GWh in 2019)

[Pilot Project: Air Handling Units](#page-6-0) ([AHU\)](#page-6-0)

AHU Control Problem

Controlled Variables

- Zone air temperature (range 15-24 degrees)
- Supply air temperature (15-30) degrees)

Manipulated Variables

- Outside and return air dampers
- Fan speed
- Heating and cooling coils

AHU Control Problem

A classical controls approach would be to use cascaded PID controllers:

We are forced to choose specific setpoints (which we can try to vary to minimize energy consumption). However, this is not easy to do without introducing dynamic interactions.

We would like to have a controller that:

- Can express the control objectives in terms of ranges and constraints
- Can explicitly take into account energy consumption
- Can easily take into account present and even future process disturbances (for example, via a weather forecast)

[Model Predictive Control \(MPC\)](#page-9-0)

What is MPC?

- Want to find a set of control actions that minimizes some cost over a fixed horizon, while respecting some constraints
- Need to have some kind of dynamic plant model to predict future behavior
- Leads to an optimization problem which must be solved
- Apply the first of the sequence of control actions, then repeat the process!

Open loop or Closed loop?

$$
\min_{\mathbf{d},\mathbf{\omega},\epsilon,\mathsf{T}} \sum_{k=0}^{N} P_{f}(\omega_{k}) + P_{h}(\mathsf{T}_{k+1}^{ha}) + P_{c}(\mathsf{T}_{k+1}^{ca}) + r_{sp}(\mathsf{T}_{k}^{za} - \mathsf{T}_{sp}^{za})^{2} + \mathsf{r}^{\mathsf{T}} \epsilon^{2}
$$
\ns.t $\mathsf{T}_{k+1}^{za} = f_{za}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{sa}, \mathsf{T}_{k}^{oa}, \omega_{k}), \mathsf{T}_{k+1}^{ma} = f_{ma}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{oa}, d_{k}^{oa}), \mathsf{T}_{k+1}^{sa} = f_{fan}(\mathsf{T}_{k}^{ca})$ \n
$$
\mathsf{T}_{k+1}^{ca} - \epsilon_{ha} \leq \mathsf{T}_{k+1}^{ha} \leq \mathsf{T}_{ha}^{max} + \epsilon_{ha}, \mathsf{T}_{ca}^{min} - \epsilon_{ca} \leq \mathsf{T}_{k+1}^{ca} \leq \mathsf{T}_{k+1}^{ha} + \epsilon_{ca}
$$
\n
$$
\mathsf{T}_{sa}^{min} - \epsilon_{sa} \leq \mathsf{T}_{k+1}^{sa} \leq \mathsf{T}_{sa}^{ma} + \epsilon_{sa}, \mathsf{T}_{za}^{min} - \epsilon_{za} \leq \mathsf{T}_{ka}^{za} + \epsilon_{za}
$$
\n
$$
d_{oa}^{min} \leq d_{k}^{oa} \leq d_{oa}^{max}, \omega^{min} \leq \omega_{k} \leq \omega^{max}
$$
\n
$$
-\dot{d}_{oa} \leq d_{k+1}^{oa} - d_{k}^{oa} \leq \dot{d}_{oa}, -\dot{\omega} \leq \omega_{k+1} - \omega_{k} \leq \dot{\omega}
$$
\n
$$
-\dot{\mathsf{T}}_{ca}^{ca} \leq \mathsf{T}_{k+1}^{ca} - \mathsf{T}_{k}^{ca} \leq \dot{\mathsf{T}}_{ca}^{ca}, -\dot{\mathsf{T}}_{ha}^{ha} \leq \mathsf{T}_{ka+1}^{ha} - \mathsf{T}_{k}^{ha} \leq \dot{\mathsf{T}}_{ha}^{ha}
$$
\n
$$
\mathsf{T}_{za}[0] = \mathsf{T}_{za}^{init}, \mathsf{T}_{ma}[0] = \mathsf{T}_{ma}^{init}, \math
$$

Complete formulation for the AHU

$$
\min_{\mathbf{d},\mathbf{\omega},\epsilon,\mathbf{T}} \sum_{k=0}^{N} P_{f}(\omega_{k}) + P_{h}(\mathcal{T}_{k+1}^{ha}) + P_{c}(\mathcal{T}_{k+1}^{ca}) + r_{sp}(\mathcal{T}_{k}^{za} - \mathcal{T}_{sp}^{za})^{2} + \mathbf{r}^{T} \epsilon^{2}
$$
\ns.t
$$
T_{k+1}^{za} = f_{za}(\mathcal{T}_{,k}^{za}, \mathcal{T}_{k}^{sa}, \mathcal{T}_{k}^{oa}, \omega_{k}), T_{k+1}^{ma} = f_{ma}(\mathcal{T}_{k}^{za}, \mathcal{T}_{k}^{oa}, d_{k}^{oa}), T_{k+1}^{sa} = f_{fan}(\mathcal{T}_{k}^{ca})
$$
\n
$$
T_{k+1}^{ca} - \epsilon_{ha} \leq T_{k+1}^{ha} \leq T_{ha}^{max} + \epsilon_{ha}, T_{ca}^{min} - \epsilon_{ca} \leq T_{k+1}^{ca} \leq T_{k+1}^{ha} + \epsilon_{ca}
$$
\n
$$
T_{sa}^{min} - \epsilon_{sa} \leq T_{k+1}^{sa} \leq T_{sa}^{max} + \epsilon_{sa}, T_{za}^{min} - \epsilon_{za} \leq T_{k+1}^{za} \leq T_{za}^{max} + \epsilon_{za}
$$
\n
$$
d_{oa}^{min} \leq d_{k}^{oa} \leq d_{oa}^{max}, \omega^{min} \leq \omega_{k} \leq \omega^{max}
$$
\n
$$
- \dot{d}_{oa} \leq d_{k+1}^{oa} - d_{k}^{oa} \leq \dot{d}_{oa}, -\dot{\omega} \leq \omega_{k+1} - \omega_{k} \leq \dot{\omega}
$$
\n
$$
- \dot{T}_{ca}^{ca} \leq T_{k+1}^{ca} - T_{k}^{ca} \leq \dot{T}_{ca}^{ca}, -\dot{T}_{ha}^{ha} \leq T_{k+1}^{ha} - T_{h}^{ha} \leq \dot{T}_{ha}^{ha}
$$
\n
$$
T_{za}[0] = T_{za}^{init}, T^{ma}[0] = T_{ma}^{init}, T_{ha}[0] = T_{ha}^{init},
$$
\n
$$
T_{ca}[0] = T_{ca}^{init}, \epsilon_{sa} > 0, \epsilon_{za} > 0, \epsilon_{ca} > 0,
$$

Cost function: Energy consumption

$$
\min_{\mathbf{d},\omega,\epsilon,\mathsf{T}} \sum_{k=0}^{N} P_f(\omega_k) + P_h(T_{k+1}^{ha}) + P_c(T_{k+1}^{ca}) + r_{sp}(T_k^{za} - T_{sp}^{za})^2 + \mathbf{r}^T \epsilon^2
$$
\ns.t $T_{k+1}^{za} = f_{za}(T_{,k}^{za}, T_k^{sa}, T_k^{oa}, \omega_k), T_{k+1}^{ma} = f_{ma}(T_k^{za}, T_k^{ca}, d_k^{oa}), T_{k+1}^{sa} = f_{fan}(T_k^{ca})$
\n $T_{k+1}^{ca} - \epsilon_{ha} \le T_{k+1}^{ha} \le T_{ha}^{max} + \epsilon_{ha}, T_{ca}^{min} - \epsilon_{ca} \le T_{k+1}^{ca} \le T_{k+1}^{ha} + \epsilon_{ca}$
\n $T_{sa}^{min} - \epsilon_{sa} \le T_{k+1}^{sa} \le T_{sa}^{max} + \epsilon_{sa}, T_{za}^{min} - \epsilon_{za} \le T_{k+1}^{za} \le T_{za}^{max} + \epsilon_{za}$
\n $d_{oa}^{min} \le d_k^{oa} \le d_{oa}^{max}, \omega^{min} \le \omega_k \le \omega^{max}$
\n $-\dot{d}_{oa} \le d_{k+1}^{oa} - d_k^{oa} \le \dot{d}_{oa}, -\dot{\omega} \le \omega_{k+1} - \omega_k \le \dot{\omega}$
\n $-\dot{T}^{ca} \le T_{k+1}^{ca} - T_k^{ca} \le \dot{T}^{ca}, -\dot{T}^{ha} \le T_{k+1}^{ha} - T_k^{ha} \le \dot{T}^{ha}$
\n $T_{za}[0] = T_{za}^{init}, T^{ma}[0] = T_{ma}^{init}, T_{ha}[0] = T_{ha}^{init},$
\n $T_{ca}[0] = T_{ca}^{init}, \epsilon_{sa} > 0, \epsilon_{za} > 0, \epsilon_{ca} > 0, \epsilon_{ha} > 0, r > 0$

Evolution of system states (based on model)

$$
\min_{\mathbf{d},\omega,\epsilon,\mathsf{T}} \sum_{k=0}^{N} P_f(\omega_k) + P_h(T_{k+1}^{ha}) + P_c(T_{k+1}^{ca}) + r_{sp}(T_k^{za} - T_{sp}^{za})^2 + r^T \epsilon^2
$$
\ns.t $T_{k+1}^{za} = f_{za}(T_{,k}^{za}, T_k^{sa}, T_k^{oa}, \omega_k), T_{k+1}^{ma} = f_{ma}(T_k^{za}, T_k^{oa}, d_k^{oa}), T_{k+1}^{sa} = f_{fan}(T_k^{ca})$ \n $T_{k+1}^{ca} - \epsilon_{ha} \leq T_{k+1}^{ha} \leq T_{ha}^{max} + \epsilon_{ha}, T_{ca}^{min} - \epsilon_{ca} \leq T_{k+1}^{ca} \leq T_{k+1}^{ha} + \epsilon_{ca}$ \n $T_{sa}^{min} - \epsilon_{sa} \leq T_{k+1}^{sa} \leq T_{sa}^{max} + \epsilon_{sa}, T_{za}^{min} - \epsilon_{za} \leq T_{k+1}^{za} \leq T_{za}^{max} + \epsilon_{za}$ \n $d_{oa}^{min} \leq d_k^{oa} \leq d_{oa}^{max}, \omega^{min} \leq \omega_k \leq \omega^{max}$ \n $- \dot{d}_{oa} \leq d_{k+1}^{oa} - d_k^{oa} \leq \dot{d}_{oa}, -\dot{\omega} \leq \omega_{k+1} - \omega_k \leq \dot{\omega}$ \n $- \dot{T}_{ca}^{ca} \leq T_{k+1}^{ca} - T_k^{ca} \leq \dot{T}_{ca}, -\dot{T}_{ha}^{ha} \leq T_{ka+1}^{ha} - T_k^{ha} \leq \dot{T}_{ha}^{ha}$ \n $T_{za}[0] = T_{za}^{init}, T^{ma}[0] = T_{ma}^{init}, T_{ha}[0] = T_{ha}^{init},$ \n $T_{ca}[0] = T_{ca}^{init}, \epsilon_{sa} > 0, \epsilon_{za} > 0, \epsilon_{ca} > 0, \epsilon_{ha} > 0, r > 0$

Actuator constraints (hard) and state constraints (soft)

$$
\min_{\mathbf{d},\mathbf{\omega},\epsilon,\mathsf{T}} \sum_{k=0}^{N} P_{f}(\omega_{k}) + P_{h}(\mathsf{T}_{k+1}^{ha}) + P_{c}(\mathsf{T}_{k+1}^{ca}) + r_{sp}(\mathsf{T}_{k}^{za} - \mathsf{T}_{sp}^{za})^{2} + \mathsf{r}^{\mathsf{T}}\epsilon^{2}
$$
\ns.t $\mathsf{T}_{k+1}^{za} = f_{za}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{sa}, \mathsf{T}_{k}^{oa}, \omega_{k}), \mathsf{T}_{k+1}^{ma} = f_{ma}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{oa}, d_{k}^{oa}), \mathsf{T}_{k+1}^{sa} = f_{fan}(\mathsf{T}_{k}^{ca})$ \n
$$
\mathsf{T}_{k+1}^{ca} - \epsilon_{ha} \leq \mathsf{T}_{k+1}^{ha} \leq \mathsf{T}_{ha}^{max} + \epsilon_{ha}, \mathsf{T}_{ca}^{min} - \epsilon_{ca} \leq \mathsf{T}_{k+1}^{ca} \leq \mathsf{T}_{k+1}^{ha} + \epsilon_{ca}
$$
\n
$$
\mathsf{T}_{sa}^{min} - \epsilon_{sa} \leq \mathsf{T}_{k+1}^{sa} \leq \mathsf{T}_{sa}^{ma} + \epsilon_{sa}, \mathsf{T}_{za}^{min} - \epsilon_{za} \leq \mathsf{T}_{ka}^{za} + \epsilon_{za}
$$
\n
$$
d_{oa}^{min} \leq d_{k}^{oa} \leq d_{oa}^{max}, \omega^{min} \leq \omega_{k} \leq \omega^{max}
$$
\n
$$
-d_{oa} \leq d_{k+1}^{oa} - d_{k}^{oa} \leq d_{oa}, -\dot{\omega} \leq \omega_{k+1} - \omega_{k} \leq \dot{\omega}
$$
\n
$$
-\dot{\mathsf{T}}_{sa}^{ca} \leq \mathsf{T}_{ka+1}^{ca} - \mathsf{T}_{k}^{ca} \leq \dot{\mathsf{T}}_{sa}^{ca}, -\dot{\mathsf{T}}_{ka}^{ha} \leq \mathsf{T}_{ka+1}^{ha} - \mathsf{T}_{ka}^{ha} \leq \dot{\mathsf{T}}_{ba}^{ha}
$$
\n
$$
\mathsf{T}_{za}[0] = \mathsf{T}_{za}^{init}, \mathsf{T}_{ma}[0] = \mathsf{T}_{ma}^{init}, \mathsf{T}_{ha}[
$$

Rate of change constraints

$$
\min_{\mathbf{d},\mathbf{\omega},\epsilon,\mathsf{T}} \sum_{k=0}^{N} P_{f}(\omega_{k}) + P_{h}(\mathsf{T}_{k+1}^{ha}) + P_{c}(\mathsf{T}_{k+1}^{ca}) + r_{sp}(\mathsf{T}_{k}^{za} - \mathsf{T}_{sp}^{za})^{2} + \mathsf{r}^{\mathsf{T}} \epsilon^{2}
$$
\n
$$
\text{s.t} \quad \mathsf{T}_{k+1}^{za} = f_{za}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{sa}, \mathsf{T}_{k}^{oa}, \omega_{k}), \mathsf{T}_{k+1}^{ma} = f_{ma}(\mathsf{T}_{k}^{za}, \mathsf{T}_{k}^{oa}, d_{k}^{oa}), \mathsf{T}_{k+1}^{sa} = f_{fan}(\mathsf{T}_{k}^{ca})
$$
\n
$$
\mathsf{T}_{k+1}^{ca} - \epsilon_{ha} \leq \mathsf{T}_{k+1}^{ha} \leq \mathsf{T}_{ha}^{max} + \epsilon_{ha}, \mathsf{T}_{ca}^{min} - \epsilon_{ca} \leq \mathsf{T}_{k+1}^{ca} \leq \mathsf{T}_{k+1}^{ha} + \epsilon_{ca}
$$
\n
$$
\mathsf{T}_{sa}^{min} - \epsilon_{sa} \leq \mathsf{T}_{k+1}^{sa} \leq \mathsf{T}_{sa}^{ma} + \epsilon_{sa}, \mathsf{T}_{za}^{min} - \epsilon_{za} \leq \mathsf{T}_{ka}^{za} + \epsilon_{za}
$$
\n
$$
d_{oa}^{min} \leq d_{k}^{oa} \leq d_{oa}^{max}, \omega^{min} \leq \omega_{k} \leq \omega^{max}
$$
\n
$$
-\dot{d}_{oa} \leq d_{k+1}^{oa} - d_{k}^{oa} \leq \dot{d}_{oa}, -\dot{\omega} \leq \omega_{k+1} - \omega_{k} \leq \dot{\omega}
$$
\n
$$
-\dot{\mathsf{T}}_{ca}^{ca} \leq \mathsf{T}_{k+1}^{ca} - \mathsf{T}_{k}^{ca} \leq \mathsf{T}_{ca}, -\dot{\mathsf{T}}_{ha}^{ha} \leq \mathsf{T}_{ka+1}^{ha} - \mathsf{T}_{k}^{ha} \leq \dot{\mathsf{T}}_{ha}^{ha}
$$
\n
$$
\mathsf{T}_{za}[0] = \mathsf{T}_{za}^{init}, \mathsf{T}_{ma}[0] = \mathsf{T}_{ma}^{init
$$

Initial conditions: the latest process value samples

AHU Model Derivation

Plant dynamics are first-principles models based on mass and energy balances. For example, zone air f_{z} :

$$
C_z \frac{dT_{Za}}{dt} = \dot{m}_{sa}^{in} C_{pa} T_{sa} - \dot{m}_{sa}^{out} C_{pa} T_{za} + \alpha (T_{oa} - T_{za}) + q(t)
$$

Actuator power consumption also based on simple models, for example cooling coil power:

$$
P_c = \frac{\dot{m}_{sa}C_{pa}(T_{ha} - T_{ca})}{\eta_c COP_c}
$$

Fan power model:

October 5, 2023 [Advanced Control for Energy Optimization](#page-0-0) 19

[Implementation](#page-19-0)

Implementation

The process models are simple and continuous, but nonlinear. The MPC optimization problem is a Nonlinear Program (NLP) Not realistic to implement solver on classic PLC. Instead, implement in Python and run on remote server. Solve with CasADI and IPOPT

Communication between PLC and MPC is through OPC UA. We keep cascade PID, and add tracking mode for bumpless switch to/from MPC

OPC UA

cs-ccr-scada001

Model Predictive Controller (Python)

GPN host internet in the property internet Forecast manager(Pythor Stormglass.io weather forecast API **HTTPP** HTTPP HTTPP HTTPP

JSON file transfer

cwe-513-win038

ARX 100 UARX 10001 cfp-2175- USSR1-401

cs-ccr-cvlhc1

WinCC OA SCADA

TSPP" TSPP"

S7 S7

Simatic NET OPC UA server

PLC UARX 10002 cfp-2175- USSR1-403

[Virtual Commissioning](#page-21-0)

Virtual Commissioning

Need a more realistic model to reliably develop and test the new controller. Created in EcosimPro:

Recreate the production setup in the lab:

Lab setup includes PLCs, SCADA and Python simulation driver application.

[Results](#page-23-0)

Simulation Studies

- Using the virtual commissioning lab setup, we can simulate periods based on historical data, and compare MPC to the existing controls
- Results are conservative, as they do not account for changes in operational parameters that MPC provides (such as using wider allowable temperature ranges)

Results indicate around 20% savings could be achieved

October 5, 2023 [Advanced Control for Energy Optimization](#page-0-0) 25

Operational Deployment

HVAC for SR1 (Point 1)

- One of two AHUs in the building will be controlled by MPC
- The other retains existing controls
- Deployed mid-September 2023
- Practically no commissioning: less than 2 hours from intervention start to MPC running

October 5, 2023 [Advanced Control for Energy Optimization](#page-0-0) 26

Operational Results: Control

Operational Results: Energy Usage

UARX 10001. MPC from 13th September. Supplied cooling power = $(T_{ra} - T_{sa})C_{pa}m_a$

The two AHUs interact somewhat, and temperatures have decreased since deploying MPC, but energy savings are considerable (∼70%)

Operational Results: Comparison

UARX 10002 (original controls). Supplied cooling power (*Tra Tsa*)*Cpam^a*

Not a fair comparison as there is an issue with the dampers on this AHU! Nevertheless overall energy consumption is reduced with MPC (∼35%)

[Conclusions](#page-29-0)

Energy savings potential

- Early results show that MPC is very good at using 'free' cooling
- Difficult to achieve this with classical setpoint regulation
- Still much scope for tuning MPC parameters and changing operational parameters (thanks to tighter control)
- Need to gather more operational data, but savings of at least 20% seem achievable

Scalability

- Once initial modeling is done, easy to apply to other similar plants
- In this case, tuning with a process model seemed to be sufficient for good results on the real plant
- Computational complexity for this class of problem (NLP) not very high. Also uses open source solvers and framework, so no license costs

Operation

- Keeping existing, well-proven controls, with bumpless transfer to MPC control, was important for acceptance
- Virtual Commissioning setup crucial for smooth deployment.

