NS 18
NIAGARA SUMMIT

CONNECTING
THE WORLD

Department of Energy – Advanced Controls

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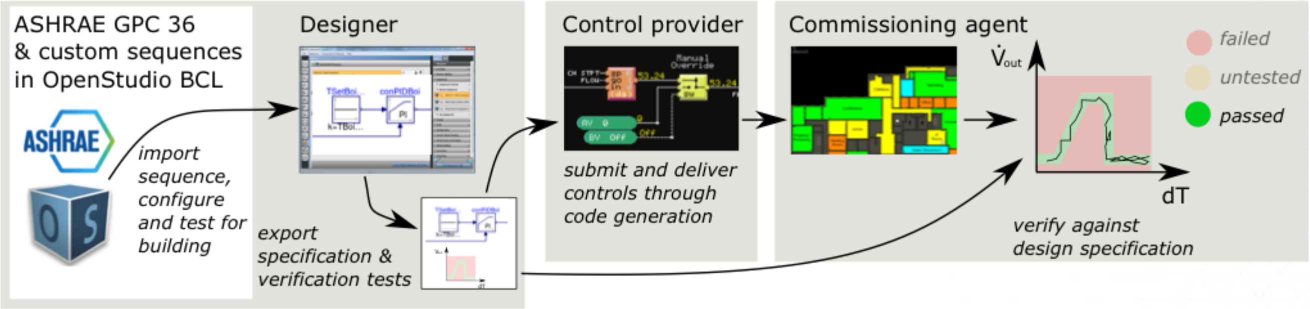
Controls Challenges

- System designers lack tools to design and validate control sequences
- Engineers sequences have to be interpreted by contractors – a process that is slow, error prone, and frustrating
- Optimized controls can save energy but are more complicated and costly to implement.
- Advanced controls are more sensitive to errors in programming, bad sensors, etc.

Solutions

- ASHRAE Guideline 36: Test and document controls best practices
- Open Building Controls: Tools to model sequences, machine readable formats, verification tools
- Adaptive Controls: Use model predictive control and machine learning to make systems self optimizing

Open Building Control: Design and implement control sequences error-free and at lower cost to owner



Codify best practice

Design

Implement

Verify against original design

BACnet standardized communication.

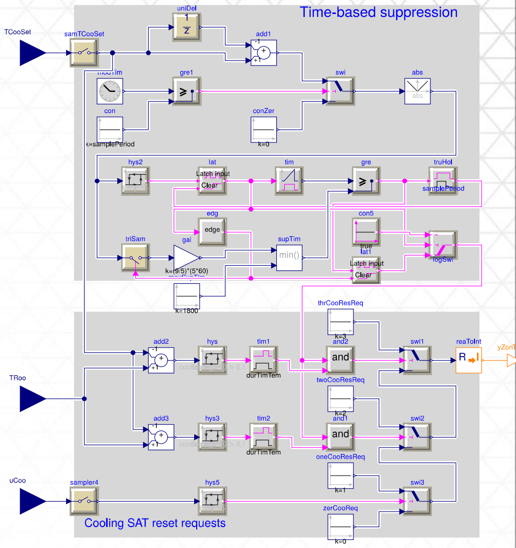
Open Building Control will standardize:

- Design: Libraries, modeling tools, electronic representation of sequences
- Delivery: Sequences can be translated instead of being interpreted
- Verification: Delivered sequence can be verified against design

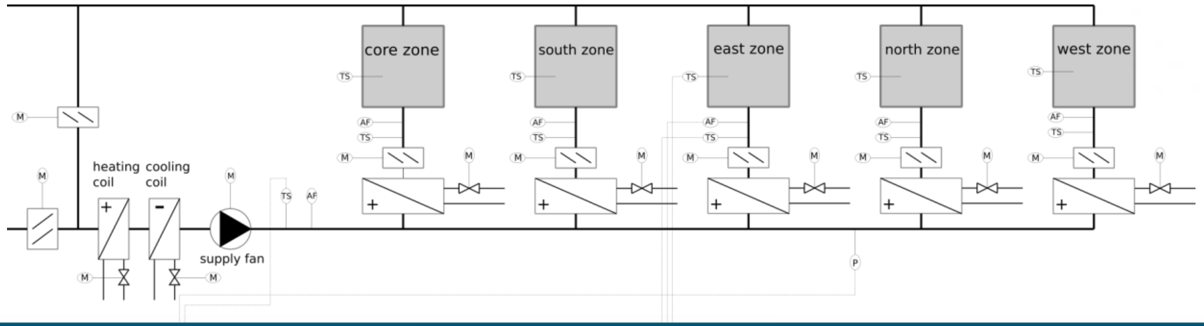
OBC Team and Status

- Project being led by Lawrence Berkeley National Lab – with funding from DOE
- Close cooperation with ASHRAE Guideline 36
- Outside project team and advisors include:
  - Leading controls system designers (Taylor, Santos, Goldschmidt, etc.)
  - Large owners (GSA, Stanford, Oracle, CBRE)
  - Controls suppliers (ALC, Distech, Tridium, etc.)
- Status: Work started in 2016, modeling tools are completed, work on translating CDL is under way.

Case study:
Multi-zone VAV controls and equipment



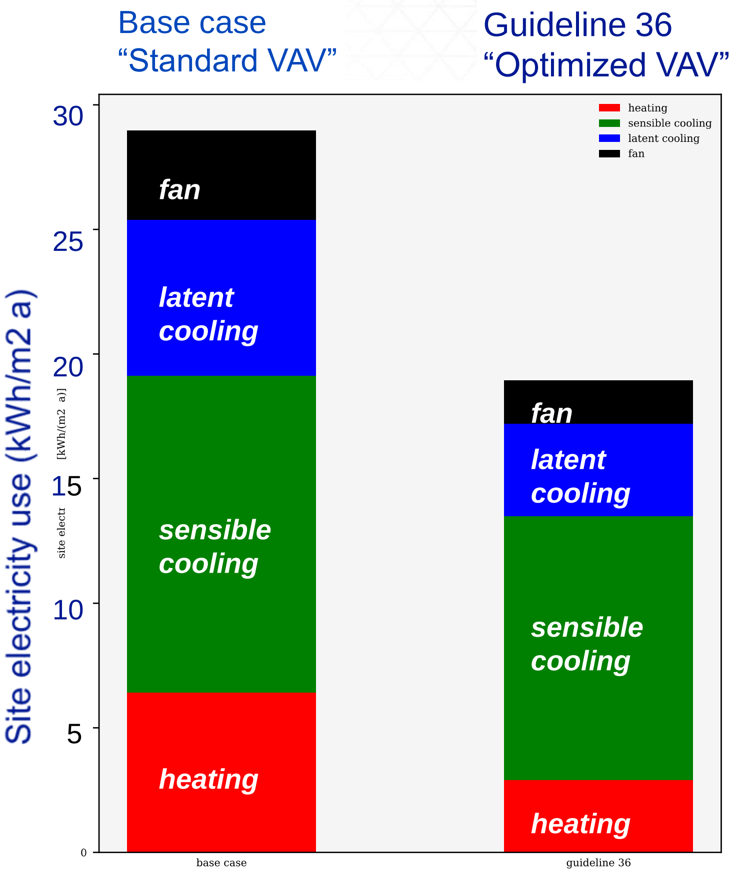
- Full airflow network.
- Wind pressure driven infiltration.
- All flows based on flow friction, damper positions and fan curves.
- 4,000 components, 40,000 variables, adaptive time step, state/time events.



Static pressure reset requests
Hot water reset requests

Modeling Results

- ~30% annual site HVAC energy savings for Chicago, solely due to controls.
- Can simulate actual control sequences, with dynamic response.
- Packaging of sequences is important, because interpretation and implementation of the sequences was more time-consuming and error-prone than anticipated.



Open Building Control Next Steps

- Simulations completed, controls description language defined
- Next step is to collaborate with controls suppliers to develop translators that will transform the CDL into their proprietary controls language
- Continued work on validation tools
- Final step is field testing

Adaptive Controls Using Machine Learning

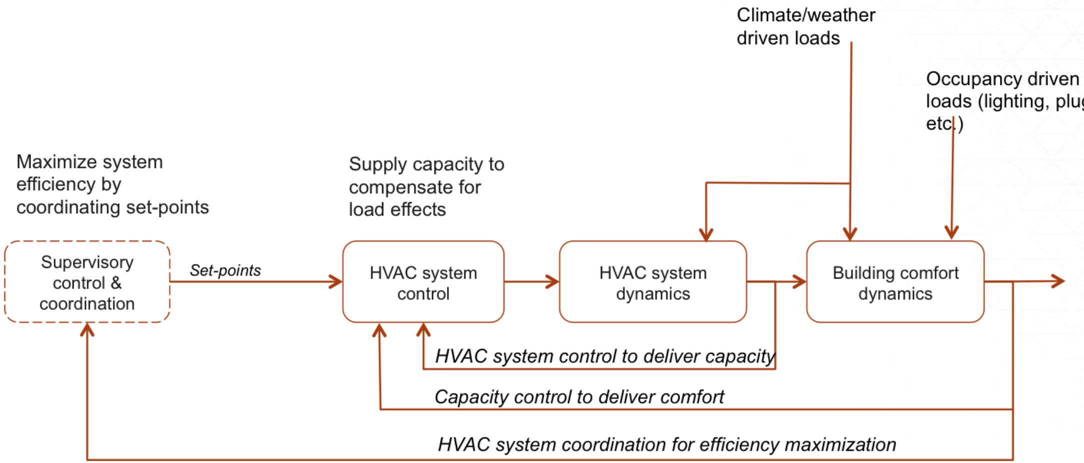
- Model Predictive Control (MPC) is the "next thing" for controls
- Systems use real world data coupled with models and simulations to learn in real time how to operate in an optimal method
- This process is being widely used in many areas – but is new for building controls
- System parameters such as comfort, capacity, etc. can be constrained in the model

Adaptive Team and Status

- Project being led by Pacific Northwest National Lab – with funding from DOE
- Project is being done in coordination with other programs related to fault detection and diagnostics
- Status: Work started in 2016, modeling and simulations are underway, next step is real world testing

Adaptive Supervisory Control

Existing typical implementations

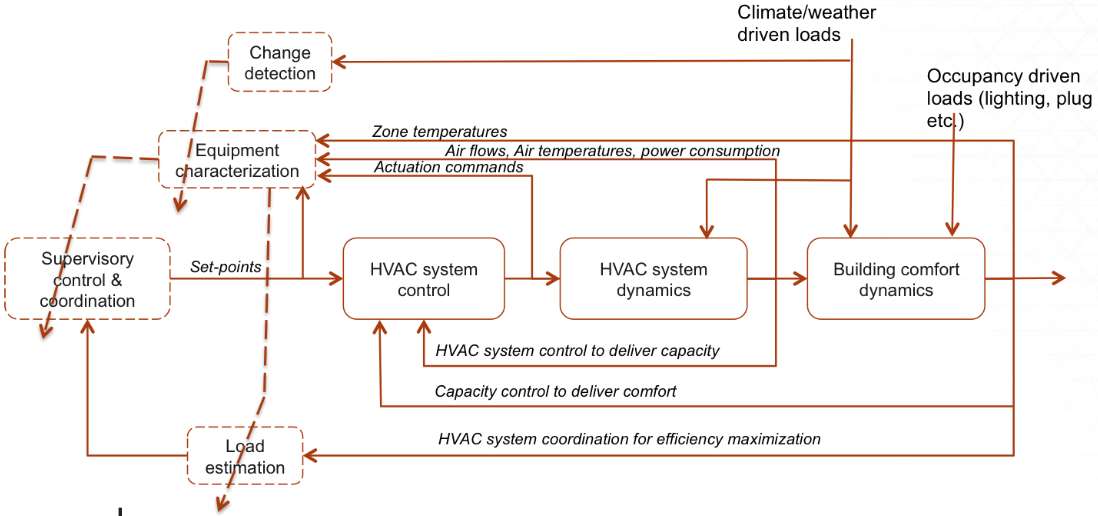


Objectives

- HVAC energy consumption reduction: >15%
- Eliminate need for manual seasonal tuning of supervisory control: self-learning
- Scalable installation process: cost-effective

Adaptive Supervisory Control

Proposed control architecture



Approach

- Automated data-driven equipment characterization and load estimation
- Set-point coordination based on robust optimization: self-optimizing
- Use of machine learning and model predictive control

Optimization Model

$$z(\Theta) = \min_{x^1,\ldots,x^K} \left\{ \sum_{t\in\mathcal{T}} (\eta_f P_f^t + \eta_h P_h^t + \eta_c P_c^t) + \lambda v^2 \right\},$$

$$\text{s.t.} \quad T_n^t = \sum_{j=1}^{q} \widehat{\alpha}_n^j T_n^{t-j} + \widehat{\beta}_n m_n^t \left(T_{s,n}^t - T_n^t\right) + \widehat{\gamma}_n T_o^t + Q_n^t,$$

$$P_f^t = \theta_0 + \theta_1 \sum_{n\in\mathcal{N}} m_n^t + \theta_2 \left(\sum_{n\in\mathcal{N}} m_n^t\right)^2 + \theta_3 p^t,$$

$$\left(p^t, \sum_{n\in\mathcal{N}} m_n^t\right) \in \widehat{\mathcal{C}},$$

$$P_h^t = \nu_h c_p \sum_{n\in\mathcal{N}} m_n^t \left(T_i^t - T_m^t\right) + c_p \sum_{n\in\mathcal{N}} \nu_n m_n^t \left(T_{s,n}^t - T_s^t\right)$$

$$P_c^t = \nu_c c_p \sum_{n\in\mathcal{N}} m_n^t \left(T_i^t - T_s^t\right),$$

$$T_r^t = \sum_{n\in\mathcal{N}} m_n^t T_n^t \Big/ \sum_{n\in\mathcal{N}} m_n^t,$$

$$T_m^t = d^t T_o^t + (1 - d^t) T_r^t,$$

$$T_n^t \geq T_n^\ell - v,$$

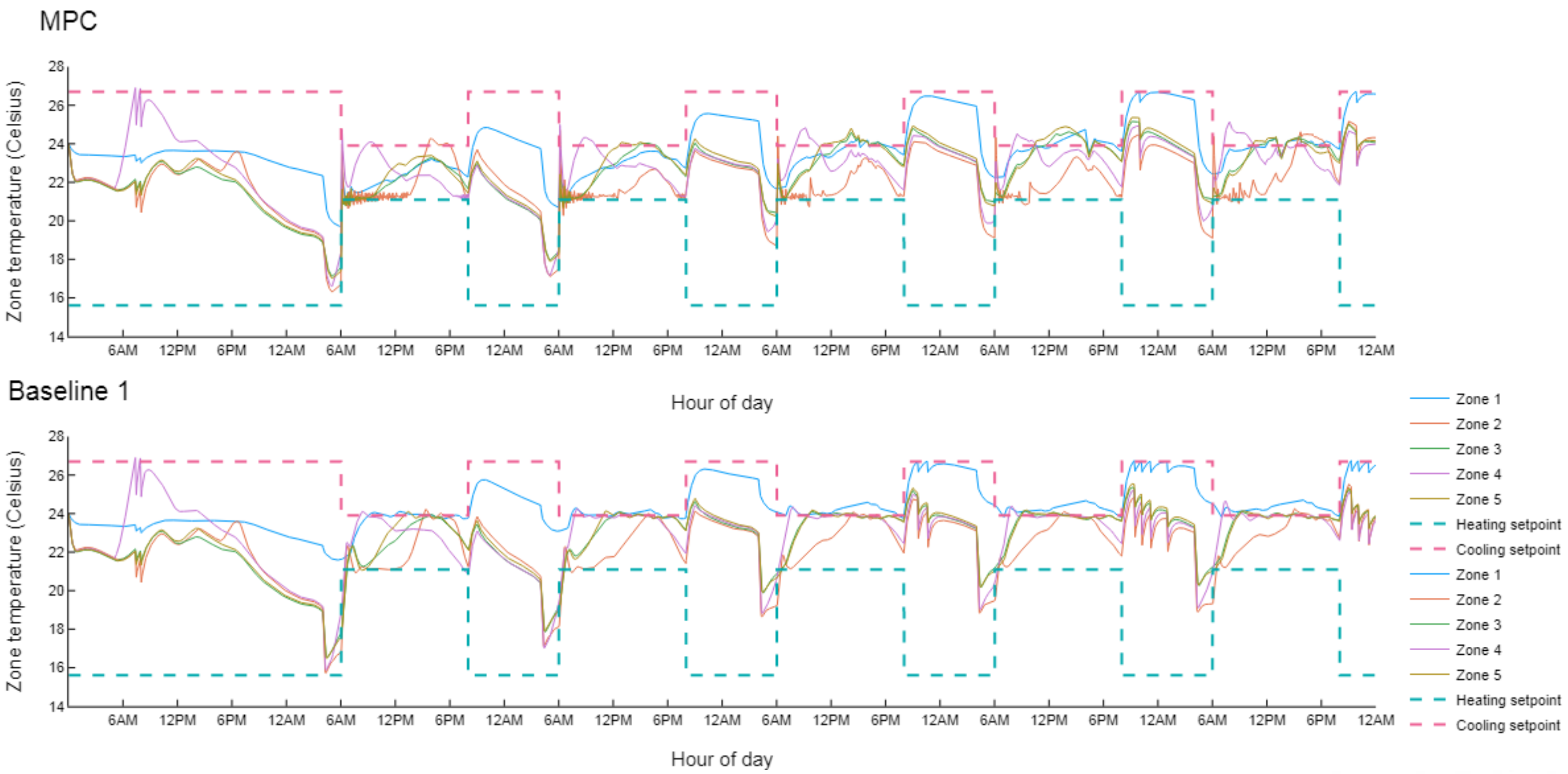
$$T_n^t \leq T_n^u + v,$$

Variable	Notation	Units	Range
Supply-air temperature	T_s^t	°C	[12.8, 70.0]
Discharge-air temperature in zone n	$T_{s,n}^t$	°C	$[T_s^t, 70.0]$
Mixed-air temperature	T_m^t	°C	$[\min\{T_o^t, T_r^t\}, \max\{T_o^t, T_r^t\}]^*$
Mass-flow rate in zone 1	m_1^t	kg/s	[1.31, 13.10]
Mass-flow rate in zone 2	m_2^t	kg/s	[0.27, 2.70]
Mass-flow rate in zone 3	m_3^t	kg/s	[0.18, 1.79]
Mass-flow rate in zone 4	m_4^t	kg/s	[0.23, 2.28]
Mass-flow rate in zone 5	m_5^t	kg/s	[0.21, 2.08]
Static pressure	p^t	Pa	[24.88, 171.70]

* Note that T_o^t is a measured variable, while T_r^t is simply an auxiliary decision.

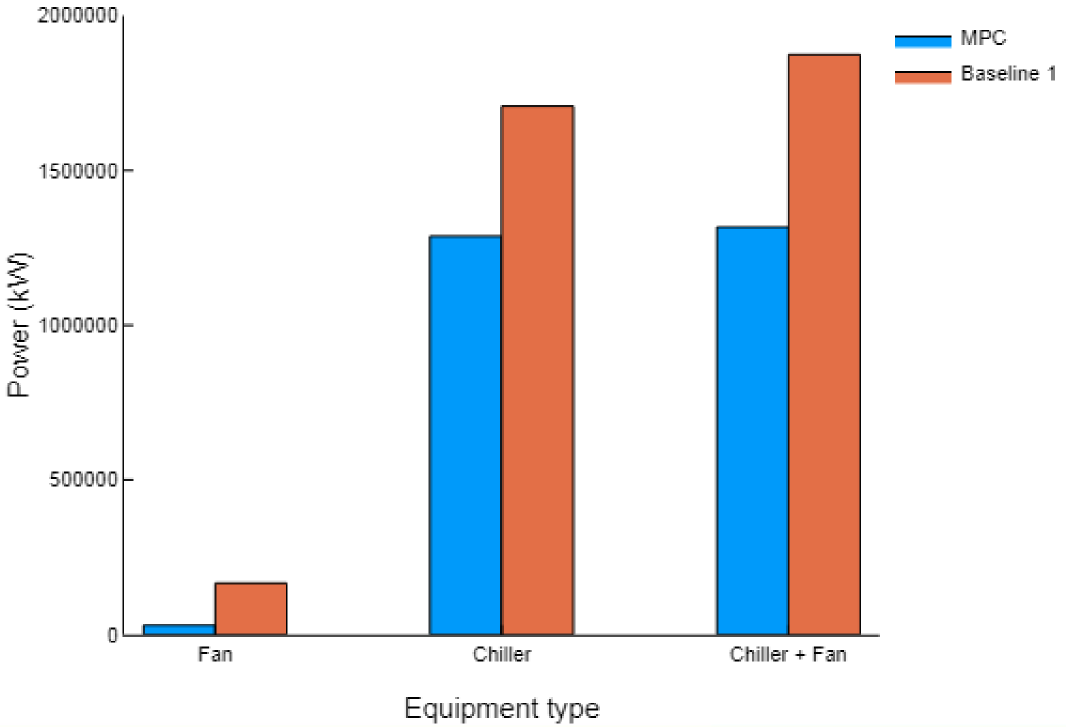
Parameter	Description	Value	Unit
K	Length of the prediction horizon	20	stage
ν_c	Efficiency of the AHU cooling coils	1.0	-
ν_h	Efficiency of the AHU heating coils	1.0	-
ν_n	Efficiency of the VAV reheat coils	1.0	-
T_n^ℓ, T_n^u	Lower and upper bounds for the zone temperatures in occupied interval	21.1, 23.9	°C
T_n^ℓ, T_n^u	Lower and upper bounds for the zone temperatures in unoccupied interval	15, 30	°C
η_f, η_h, η_c	Weights in the optimization objective	1,1,2	-
λ	Slack parameter	10^5	-

Zone temperatures (floor 1)



The model constrains comfort

Modeled Results



MPC savings over Baseline 1

1) Fan = 82 %
2) Chiller = 25 %
3) Total = 30 %

Model shows 30% improved efficiency vs optimized VAV

Next Steps for Adaptive Controls and MPC

- Additional modeling and simulations
- Deploy in advanced controls lab using PNNL developed tools

Contact Info

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