Core Research

Internship Challenge

Static Pressure & Supply Air Temp. Optimization for an Air Handling Unit (AHU)

Author : Gulai Shen, Ali Mehmani
Contact: RSCH@prescriptivedata.io

Opportunity Description 2

Introduction 3

Problem Definition 4

Challenge Questions 7

- C1: Research and investigation 7
- C2: Training and evaluating a data-driven model 7
- C3: Perform the optimization 7
- C4: Further thoughts 7

Additional Resources 8

Opportunity Description

Prescriptive Data is focused on providing cost savings and enhanced thermal comfort in built spaces through the intersection of Operational Technology (OT) with Information Technology (IT). With its flagship product Nantum OS, Prescriptive Data has responded to market demand for a next-generation building management platform that cultivates the full potential of the building operator by combining institutional knowledge with data-driven insights from IoT, big data, and the latest advances in machine learning and artificial intelligence. Prescriptive Data designs its solutions by collaborating with building operators and engineers and maintains a living lab of over 10 million square feet of New York real estate in which it vets new concepts, technologies, sensors, and applications.

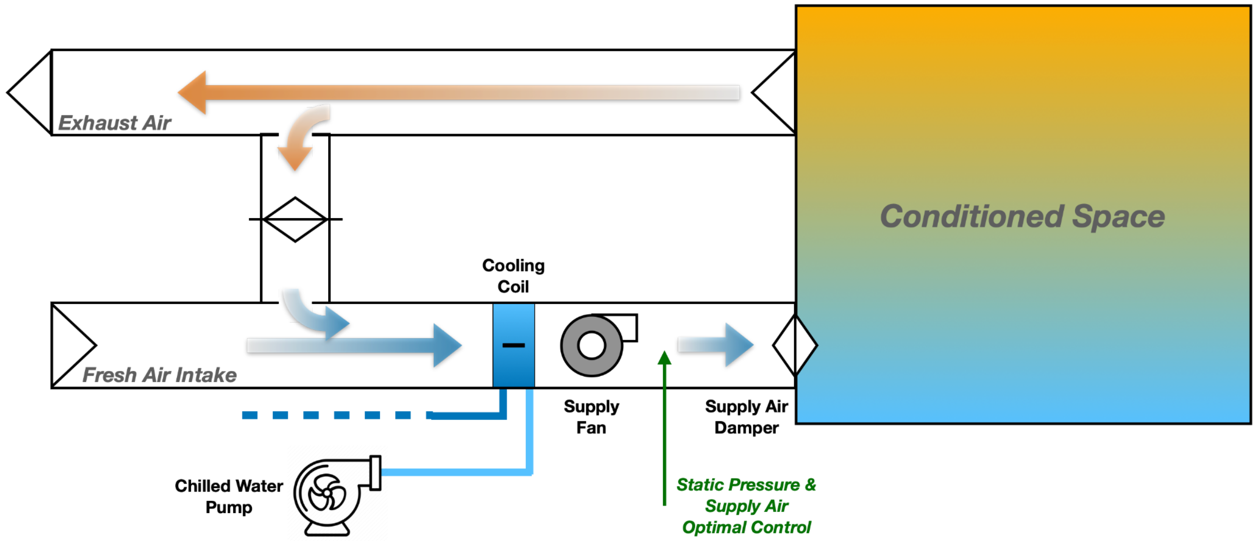
Prescriptive Data’s Core Research Team directs and implements an organization's research and development policies, objectives, and initiatives with a focus on extending Artificial Intelligence methodologies, computational techniques, methods and tools in the domain of smart-building technology.

This challenge is designed to help college researchers incorporate their knowledge and experience into the real-world problems tackling energy efficiency and many other aspects of a sustainable and smart built environment. Additionally, it aims to help researchers identify potential paths for their own research, gaps between academia and industry, as well as areas of significance they can continue to improve on.

This challenge aims to select multiple candidates for Prescriptive Data’s Core Research Team Summer Internship Program. The winners of the challenge will spend the summer at Prescriptive Data and be awarded a $30,000 scholarship.

Introduction

A typical Air Handling Unit (AHU) with Variable Air Volumes (VAV) transfers cooled air that passes through the Chilled Water (CHW) coils to the interior spaces during cooling seasons. A typical system can be simplified and visualized here:



To control a system like this, multiple setpoints can be adjusted according to the conditions of weather and building. Considering the following parts:

- Chilled Water (CHW) Pump: it pumps chilled water from the chiller to the CHW coils and returns back to the chiller, absorbing the heat in the air though the coils.
- CHW Valve: it modulates the amount of CHW through the coil. A 100% open CHW valve means that is insufficient cooling to that specific AHU, and a 0% open CHW valve means the AHU needs 0 cooling. It is desired to have the valve wide but not fully open (95-98%) for maximum efficiency.
- Cooling/CHW Coil: it is like a shell and tube heat exchanger which exchanges heat between air and CHW to cool down the air before it reaches the air conditioned spaces.
- Supply Fan: AHU fan circulates the air, bringing cooled and fresh air to space and extracting hot air from the space. A typical AHU sees one fan or one supply fan and one return fan.
- Supply Air Damper: one AHU can have multiple dampers located at each of the terminal boxes. Terminal boxes with dampers can control the amount of air into the spaces, thus are called Variable Air Volumes (VAV). Similar to the CHW valve, a 100% open damper means that is insufficient cooking to that specific terminal box, and a 0% open damper means the terminal box does not need cooling.

Problem Definition

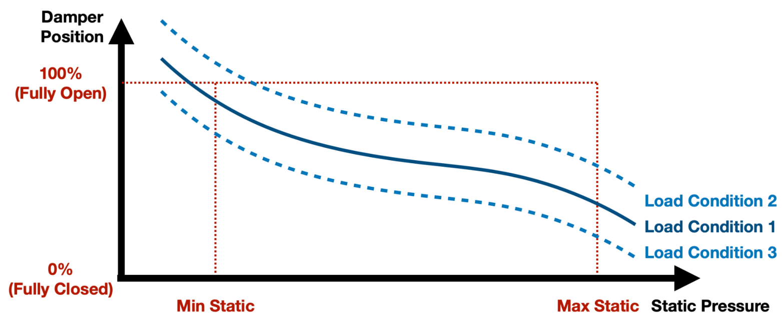
- Objective: Two equipment: the AHU fan and the CHW pump are consuming electric power and the total power is needed to be minimized at any given time.

$$Min\ P_{fan} + P_{pump}$$

- Control Variables: A typical AHU with VAV has two active setpoints that can be controlled: the static pressure setpoint (P_{static}) and the supply air temperature setpoint (T_{SA}).

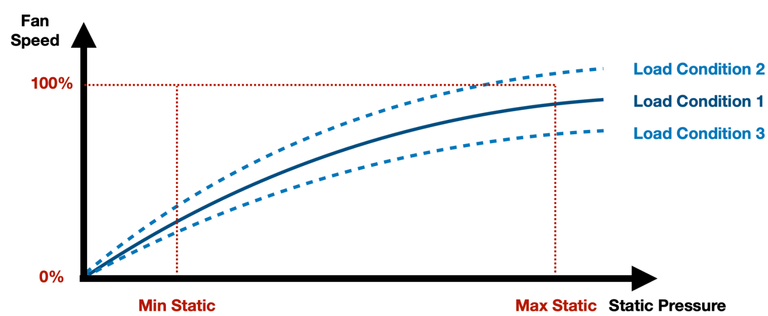
- Equality Constraints:
These models are all provided in ahu_model.py for your usage. You need to give the required inputs.You can leave the optional inputs unchanged, but also you can adjust the values to see the impacts. Next, we introduce each model one by one:

  - $Damper\ Position \sim f(P_{static})$



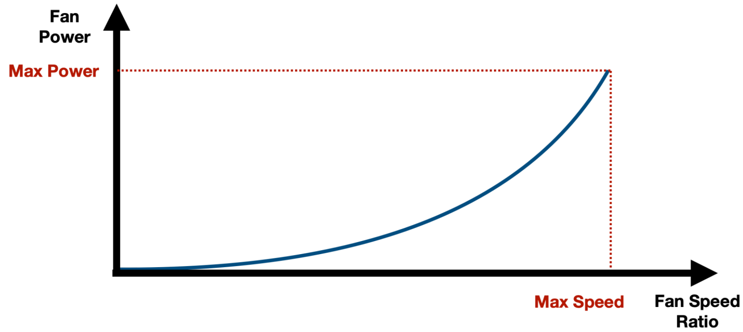
As static pressure drops, the damper has to be more open to allow the AHU to achieve the desired resistance. Use function: *damper_pos_from_static*.

  - $Fan\ Speed \sim f(P_{static})$



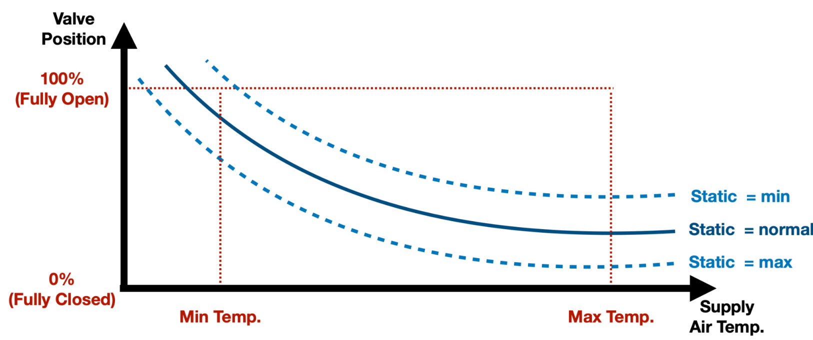
As static pressure increases, fan speed increases to maintain the desired air flow with increased resistance in the AHU. Use function: *fan_speed_from_static*.

- $Fan\ Power \sim f(Fan\ Speed)$



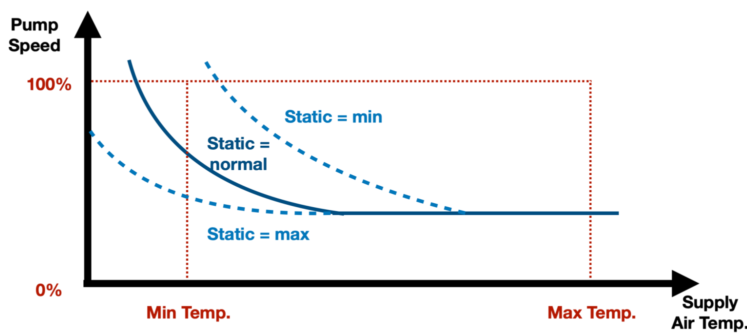
As fan speed increases, fan power consumption increases. Use function: *fan_power_from_speed*.

- $Valve\ Position\ (\%) \sim f(T_{SA},\ P_{static})$



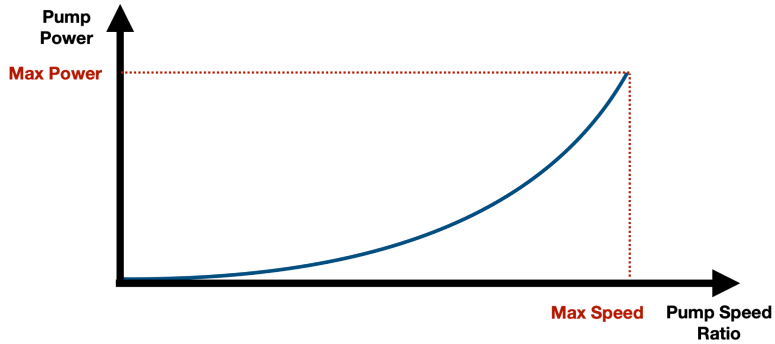
As supply air temperature drops, more chilled water is required for cooling, leading to the further opening of the chilled water valve. Use function: *valve_pos_from_Tsa_static*.

- $Pump\ Speed \sim f(T_{SA}, P_{static})$



As supply air temperature drops, after a deflection point where the chilled water valve has been fully open, the chilled water pump speed will begin to increase. Use function: *pump_speed_from_Tsa_static*.

- $Pump\ Power \sim f(Pump\ Speed)$



As pump speed increases, pump power consumption increases. Use function: *pump_power_from_speed*.

- Inequality Constraints:
  - $Damper\ Position\ <\ 1$ to prevent insufficient cooling
  - $0.15\ <\ Fan\ Speed\ <\ 1$ to protect fan motor
  - $0.3\ <=\ Pump\ Speed\ <\ 1$ to protect pump motor
  - $0.3\ <=\ P_{static}\ <= 2.5$ allowable static pressure range
  - $55 < T_{SA} < 70$ allowable supply air temp. range

Challenge Questions

C1: Research and investigation

- Provide an introduction on how the AHU with VAV works in a couple slides.

C2: Training and evaluating a data-driven model

For the Fan_power ~ f(Fan_speed) model

- Construct a valid model from the actual dataset provided.
- Compare the model you generated with the default model provided.
- Think about how to clean and filter data based on the physics info (we know there is a cubic relationship between power consumption of a fan and its speed).
- Show your results in one slide

C3: Perform the optimization

- Select an appropriate optimization method (preferably written in python, but feel free to use MatLab, GAMS, etc.), incorporating the objective, variables, and constraints described above to code an optimizer that optimizes the two setpoints at the given condition. Think about and explain the selection of the optimization methods, why is it good for applications like this? Show in one slide.
- Show the formulation of optimization in one slide, show the result of optimization in another. (try to visualize the whole design space and explain on the result and physics behind)

C4: Further thoughts

- Which of the assumptions / designs in this problem might be too ideal?
- What are some potential gaps to implement this in the real environment?
- What additional info, dimension, and others can be considered in this problem to fully optimize an AHU?

Additional Resources

Building Energy and HVAC

- HVAC System Introduction
- AHU Introduction
- Artificial Intelligence & Real Estate Information (Realcomm)
- Predictive Demand-Side Management Optimization (AEE)
- The Impact Of COVID-19 On NYC Office Buildings
- ATCO's 555 Fifth Avenue Reduces Annual Energy Use By 252,580 kWh ($43k / year) Using Nantum

Optimization

The basic form of Optimization

$$
\begin{aligned}
&min\ /\ max \quad && f(x) \\
&s.t. && g(x)\ <=\ 0 \\
& && x\ \in\ X
\end{aligned}
$$

$where$

$x\ =\ vector\ of\ variables$

$f\ =\ objective\ function$

$g\ =\ constraints$

$X\ =\ set\ of\ bounds/integrality\ constraints$

An Introduction to Optimization

Deterministic / Algebraic optimization

- LP (Solvers: CPLEX, gurobi, FICO Xpress, OSL, LOINDO,...; Algorithms: simplex algo., interior point method)
- NLP
- IP / MIP (Solvers: CPLEX, gurobi, FICO Xpress; Algorithms: branch-and-bound branch-and-cut)
- MINLP ()

Nondeterministic / Data-driven optimization

- Surrogate-based optimization (simulation-based, metamodel, black-box derivative-free…)
- Bayesian optimization (ml based)
- Gradient methods
- Population-based algorithms (PSO, brainstorm opt., firefly algo., …)

Python Optimization Packages

- Pyomo
  http://www.pyomo.org/
- Pyswams:

https://pyswarms.readthedocs.io/en/latest/intro.html
- PSO: https://github.com/nathanrooy/particle-swarm-optimization

Building Energy Optimization Literatures
- Ali Mehmani, Concurrent optimization of thermal and electric storage in commercial buildings to reduce operating cost and demand peaks under time-of-use tariffs
- Ali Mehmani, Data-enabled building energy savings (DE BES)
- Ali Mehmani, Deep learning-based real-time building occupancy detection using AMI data
- Gulai Shen, A data-driven electric water heater scheduling and control system