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# AI Powered Humidity Control: Chicago Art Institute

Lucas Dixon & Jarret Kelly, Ameresco

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ART INSTITVTE CHICAGO

# Agenda

- **Introduction of Concepts**
- **Art Museum Project**
  - Electrical Submetering
  - Machine Learning & Predictive Analytics
- **Questions and Ideation Discussion**

*Chat GPT and other Gen AI was used in the making of this presentation.*

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# Baseline

- Energy savings opportunities are everywhere.
- Existing Building Automation systems are limited in capability.
  - Building automation systems are rule based systems. They follow the same rules every day until someone changes something.
  - Building automation systems do not predict, do not learn, and do not deal well with multiple variables driving a decision.

# Take Aways

- Evaluate the buildings, projects, and operations in your “sphere of influence” differently.
- Keep an open ear, eye, and mind for opportunities to use AI tools NOW.
- Understand the concepts and tools available a bit more.

# Define Terms

- **AI : Artificial Intelligence**
  - Artificial intelligence (AI) is a set of technologies that enable computers to perform a variety of advanced functions, including the ability to see, understand and translate spoken and written language, analyze data, make recommendations, and more.
- **Generative AI= (Chat GPT)**
  - Generative artificial intelligence (AI) is a type of AI that can create new content, such as text, images, videos, and audio, based on patterns and structure learned from training dataA Model-
- **ML: Machine Learning**
  - Machine learning is a field of study within artificial intelligence (AI) that focuses on developing algorithms that can learn from data and perform tasks without explicit instructions.
- **BAS- Building automation system/Control System**
- **Training a Model**
  - Training is the process of feeding a machine learning algorithm a large amount of data and allowing it to learn the relationships and patterns in the data. The goal is to create a model, which is a mathematical function that can take in new inputs and make predictions or classifications based on the learned patterns.
- **Discharge Air Set Point**
  - The temperature that the BAS system is controlling the air handler to.

# Define Terms

- **Machine Learning (ML)** and **Artificial Intelligence (AI)** are closely related but distinct fields. Here's how they differ:
- In short, **machine learning is a subset of AI**, and it represents a key approach to achieving intelligent system.
- **1. Artificial Intelligence (AI)**
- **Definition**: AI is the broader concept of machines being able to carry out tasks in a way that we would consider “smart.” It encompasses any technique or technology that enables computers to mimic or simulate human intelligence, such as reasoning, problem-solving, learning, and adapting.
- **Scope**: AI includes various subfields, including machine learning, natural language processing, robotics, expert systems, and computer vision.
- **Examples**:
  - AI-powered personal assistants like Siri or Alexa
  - Chess-playing computers like Deep Blue
  - Autonomous systems like self-driving cars
- **2. Machine Learning (ML)**
- **Definition**: Machine Learning is a subset of AI that focuses specifically on enabling machines to learn from data. In ML, algorithms and statistical models allow computers to improve their performance on a task without being explicitly programmed to do so. Instead, they identify patterns in data and make predictions or decisions based on that data.
- **Scope**: ML is a key technique used in AI to enable systems to "learn" from data. However, it does not encompass all of AI. Other AI techniques, such as rule-based systems or hard-coded logic, do not involve machine learning.
- **Examples**:
  - Spam email filtering
  - Image recognition in photo apps (e.g., tagging people)
  - Recommender systems (e.g., Netflix or Amazon suggestions)
- **Key Differences:**

1. **AI is the broader field**, and ML is one approach used within AI to achieve intelligent behavior.
2. **AI is about enabling machines to act intelligently**, while **ML focuses on allowing machines to learn from data** to improve their performance over time.
3. **AI can use different methods**, not all of which involve learning (e.g., rule-based systems, symbolic AI), whereas ML relies entirely on data-driven learning processes.

# Predicting the Future

- **AI will**
  - Gen AI will turn HVAC SOO into BAS Code.
  - ML AI will review building operations, make suggestions, and eventually make changes automatically.
  - Implementation will be come incrementally, and maybe all at once.
- **AI will be embedded in**
  - Building automation systems generally.
  - Third party analytics or software layers.
  - Major HVAC equipment.
  - A whole new set of tools that we have/have not imagined yet.

**OFF the shelf AI tools exist NOW for CUSTOM implementation to save energy today.**

# Energy Meter Analysis

# Electrical Submeter Installation

## Submeter Installation

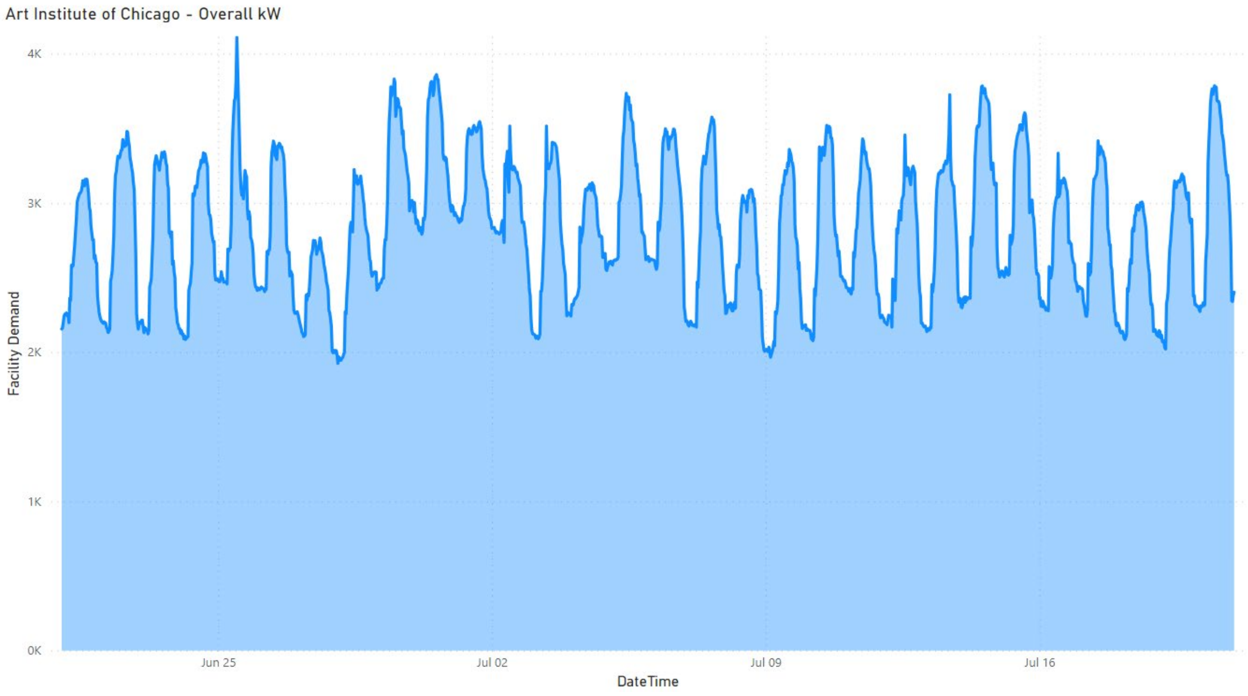
- Installed submeters at 6 locations in main electrical rooms
- Each submeter has 48 CT inputs, 16 three phase circuits, expandable.
- Metered main service, motor control centers, chillers, key panels, 49 connected loads.
- Installation required overnight shutdowns in stages
- Data flow configured to cloud based analytics engine

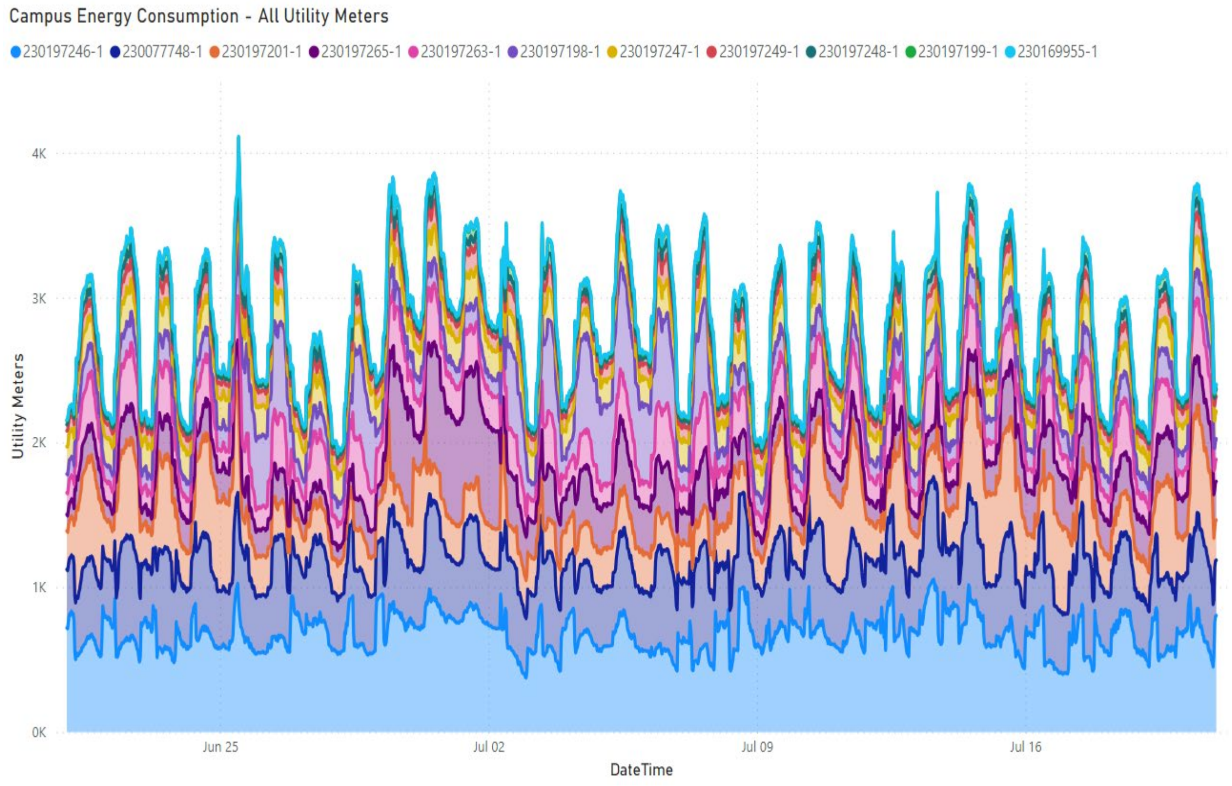


# Campus Electrical Metering Project

## Overall Metering

- Sixteen meters located on the campus, 10 with routine usage

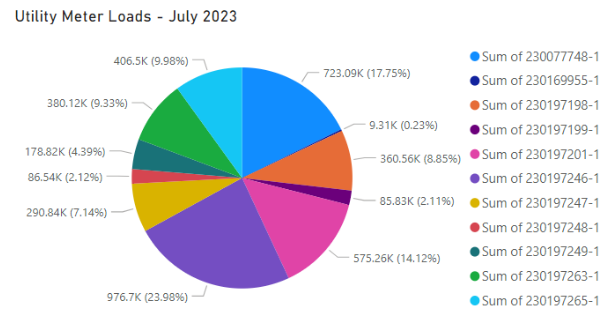


# Energy Meter Analysis

## Overall Metering

- Analysis of utility data indicated largest summer and winter meter loads
- Identified ideal electrical services for further submetering
- Captured largest loads in the building




Summer

| Meter | Meter Room | Jul 2021 kWh | Max kW | Min kW | Average kW | Daytime Average | Nighttime Average | Load Percentage |
|---|---|---|---|---|---|---|---|---|
| 230197246 | **MW055** | 600282 | 1128.6 | 150.6 | 781.6 | 806.6 | 731.6 | 25.3% |
| 230197201 | **MW051** | 444540 | 856.6 | 257.1 | 578.8 | 591.1 | 554.3 | 18.7% |
| 230077748 | **FEB44B** | 383411 | 687.0 | 393.8 | 499.2 | 540.6 | 416.6 | 16.1% |
| 230197265 | **MW055** | 207177 | 994.2 | 134.6 | 269.8 | 289.0 | 231.2 | 8.7% |
| 230197263 | **RU018** | 182081 | 366.6 | 139.8 | 237.1 | 269.4 | 172.4 | 7.7% |
| 230197198 | **MW051** | 169600 | 706.3 | 119.8 | 220.8 | 233.1 | 196.2 | 7.1% |
| 230197247 | MW055 | 154274 | 231.6 | 167.6 | 200.9 | 207.2 | 188.3 | 6.5% |
| 230197249 | MW055 | 135993 | 261.0 | 98.0 | 177.1 | 194.5 | 142.3 | 5.7% |
| 230197248 | MA034 | 48976 | 105.6 | 32.3 | 63.8 | 73.0 | 45.4 | 2.1% |
| 230197199 | MW051 | 44369 | 94.6 | 21.0 | 57.8 | 72.6 | 28.1 | 1.9% |
| 230169955 | | 4908 | 7.7 | 6.0 | 6.4 | 6.3 | 6.6 | 0.2% |
| 230164208 | | 21 | 0.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230197279 | | 8 | 16.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230169956 | | 4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230044673 | | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230169954 | | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |

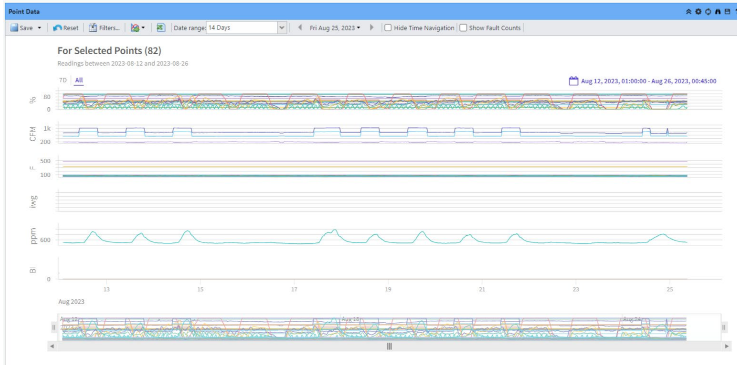
Winter

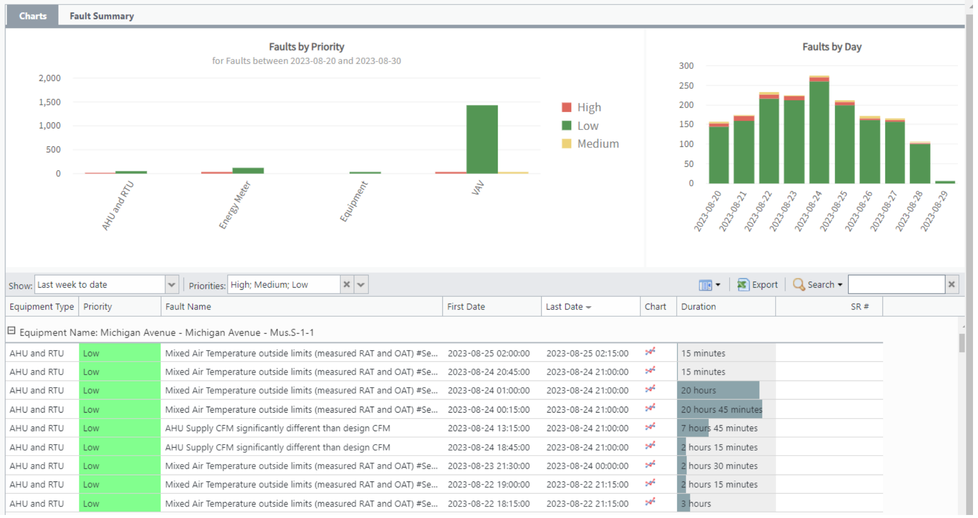
| Meter | Meter Room | Dec 2021 kWh | Max kW | Min kW | Average kW | Daytime Average | Nighttime Average | Load Percentage |
|---|---|---|---|---|---|---|---|---|
| 230077748 | **FEB44B** | 476976 | 746.6 | 461.8 | 567.8 | 605.5 | 492.4 | 20.1% |
| 230197198 | **MW051** | 295279 | 763.7 | 120.1 | 351.5 | 322.1 | 410.5 | 12.4% |
| 230197201 | **MW051** | 273171 | 832.8 | 238.8 | 325.2 | 310.7 | 354.3 | 11.5% |
| 230197263 | **RU018** | 262241 | 502.8 | 154.2 | 312.2 | 342.2 | 252.2 | 11.0% |
| 230197246 | **MW055** | 191545 | 697.2 | 4.4 | 228.0 | 273.7 | 136.7 | 8.1% |
| 230197247 | MW055 | 162412 | 239.6 | 156.6 | 193.3 | 198.0 | 184.0 | 6.8% |
| 230197249 | MW055 | 120456 | 480.6 | 82.4 | 143.4 | 152.2 | 125.9 | 5.1% |
| 230197265 | **MW055** | 73921 | 266.4 | 33.6 | 88.0 | 89.3 | 85.3 | 3.1% |
| 230197199 | MW051 | 68768 | 127.4 | 36.4 | 81.9 | 98.1 | 49.5 | 2.9% |
| 230197248 | MA034 | 64491 | 123.7 | 42.8 | 76.8 | 81.4 | 67.6 | 2.7% |
| 230169955 | | 14942 | 19.9 | 17.0 | 17.8 | 17.7 | 17.9 | 0.6% |
| 230164208 | | 23 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230169956 | | 10 | 10.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230197279 | | 7 | 14.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230044673 | | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |
| 230169954 | | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0% |

# Building Automation System Analysis

# Building Automation System Analysis

- Integration with campus Building Automation System
- Providing cloud-based data analytics
- Rules and configured to monitor data and provide alerts
- Proactive identification of energy waste or equipment fault





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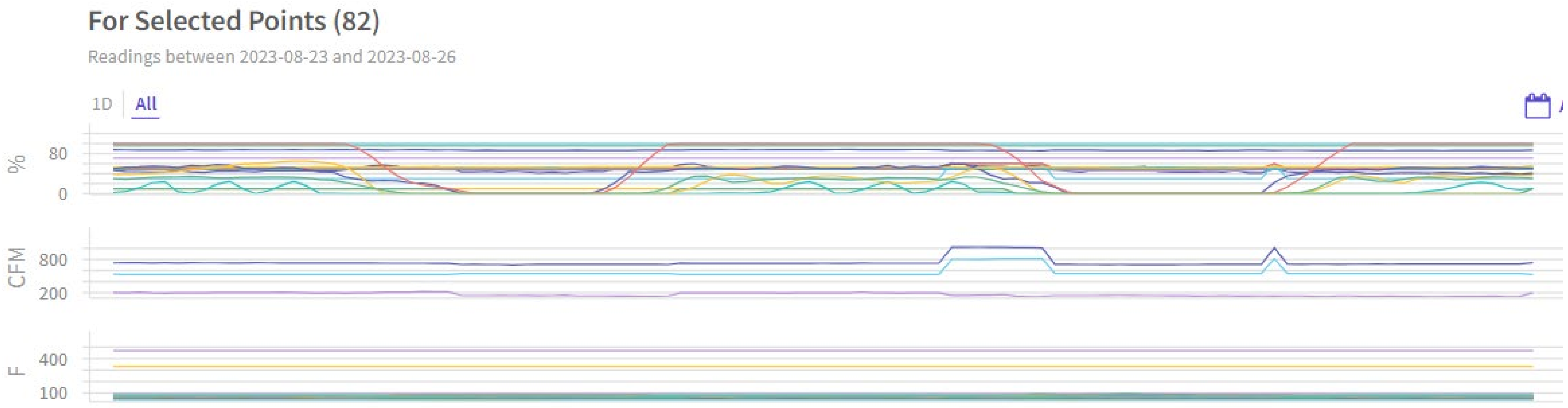
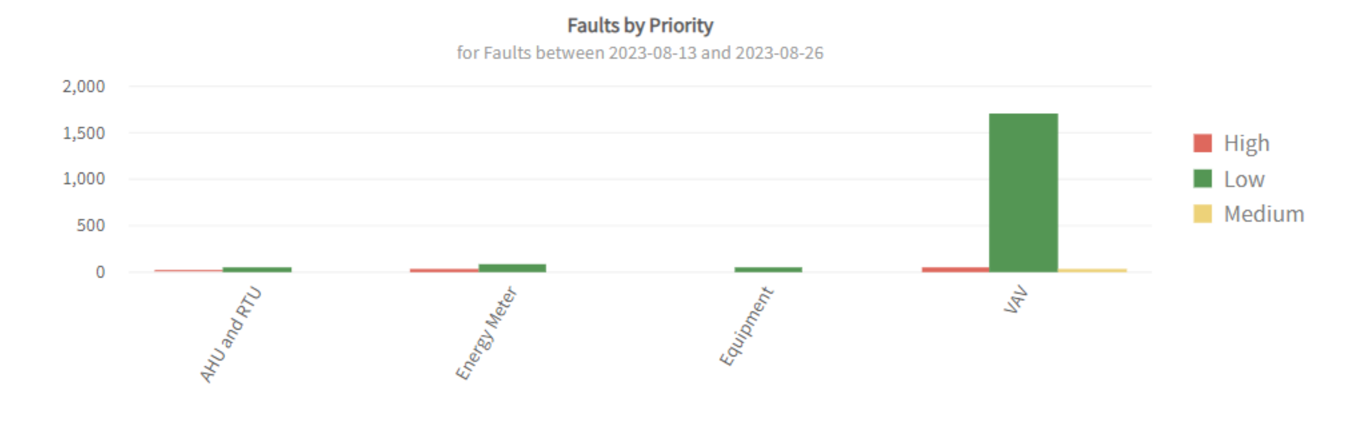
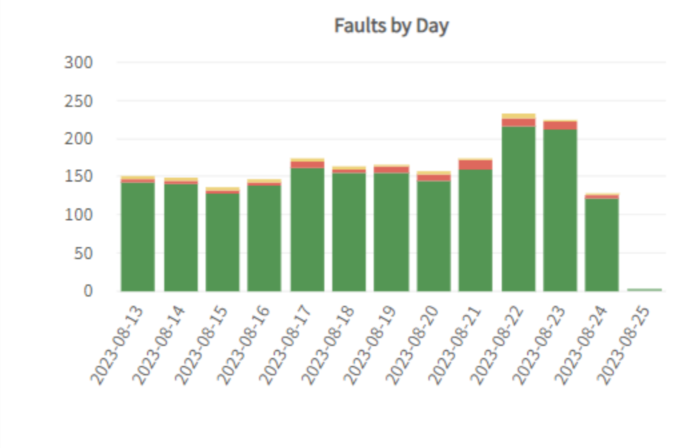
# Building Automation System Monitoring

- Data collected from Bacnet network and pushed to cloud-based monitoring platform
- Data brought into common format
- Points are tagged with common naming convention
- Rule template library, can push rules to all matching equipment
- Different priority levels established



# BAS Monitoring – Rules




Show: Last week to date | Priorities: High; Medium; Low | Export | Search

| Equipment Type | Priority | Fault Name | First Date | Last Date | Chart | Duration | SR # |
|---|---|---|---|---|---|---|---|
| Equipment Name: Michigan Avenue - Michigan Avenue - Mus.S-1-1 | | | | | | | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-25 02:00:00 | 2023-08-25 02:15:00 | | 15 minutes | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-24 00:15:00 | 2023-08-24 21:00:00 | | 20 hours 45 minutes | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-24 01:00:00 | 2023-08-24 21:00:00 | | 20 hours | |
| AHU and RTU | Low | AHU Supply CFM significantly different than design CFM | 2023-08-24 13:15:00 | 2023-08-24 21:00:00 | | 7 hours 45 minutes | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-23 21:30:00 | 2023-08-24 00:00:00 | | 2 hours 30 minutes | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-22 19:00:00 | 2023-08-22 21:15:00 | | 2 hours 15 minutes | |
| AHU and RTU | Low | Mixed Air Temperature outside limits (measured RAT and OAT) #Se... | 2023-08-22 18:15:00 | 2023-08-22 21:15:00 | | 3 hours | |
| Equipment Name: Michigan Avenue - Michigan Avenue - Mus.S-2-1 | | | | | | | |
| AHU and RTU | Low | Air Handler CFM Sensors Need Calibration #SensorError | 2023-08-24 08:30:00 | 2023-08-24 21:30:00 | | 13 hours | |

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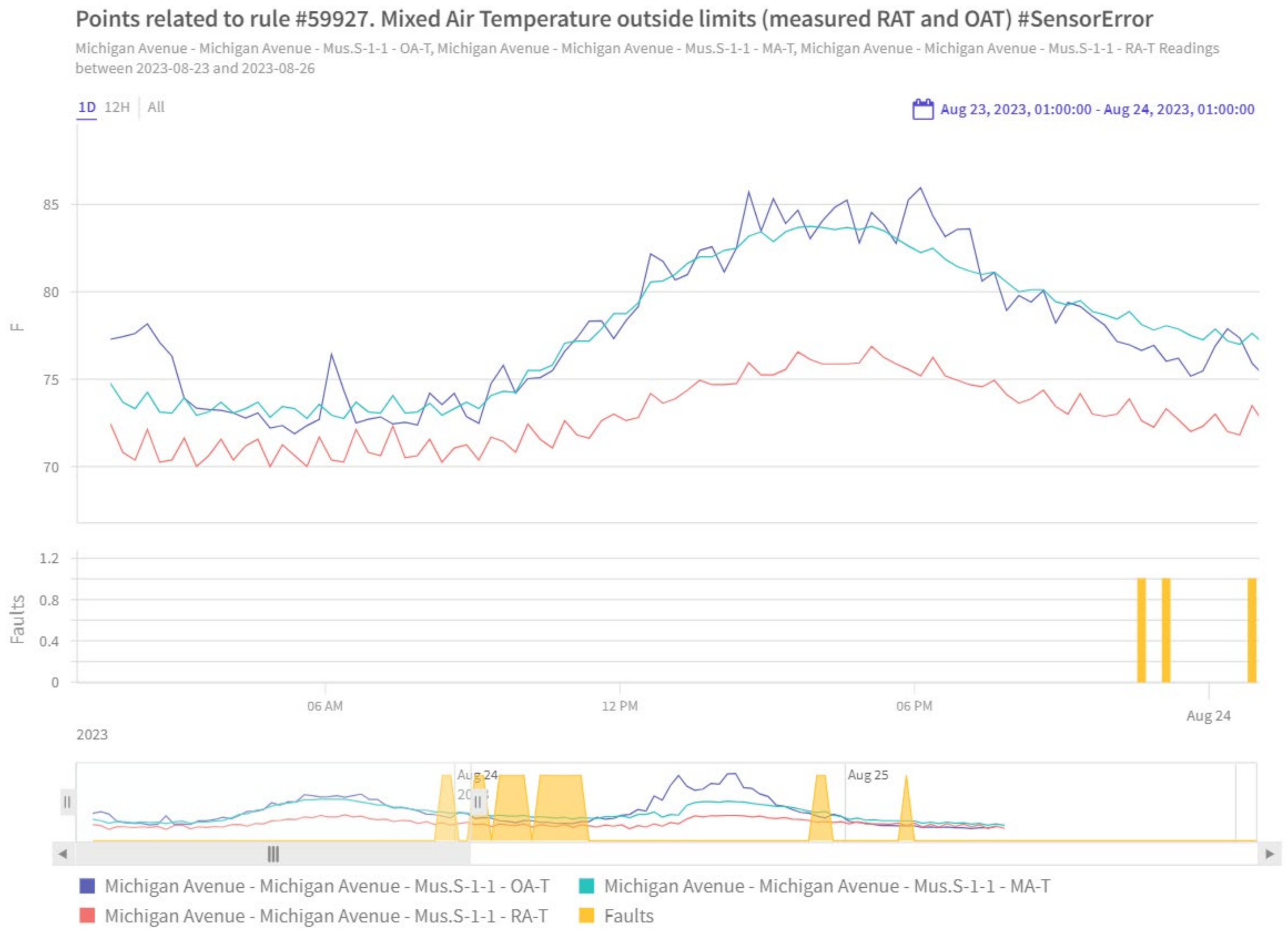
# BAS Monitoring – Rules

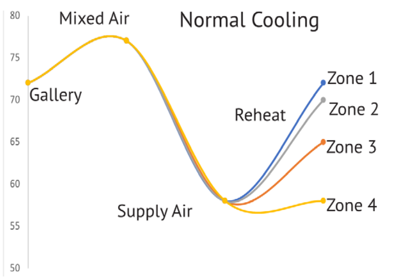


# Machine Learning & Predictive Analysis

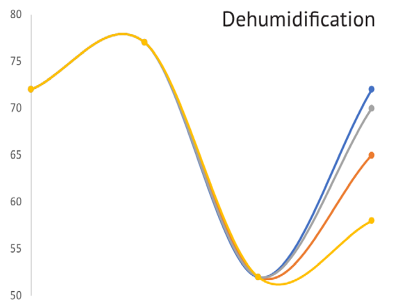
# Machine Learning and Predictive Analytics

## Concept Overview

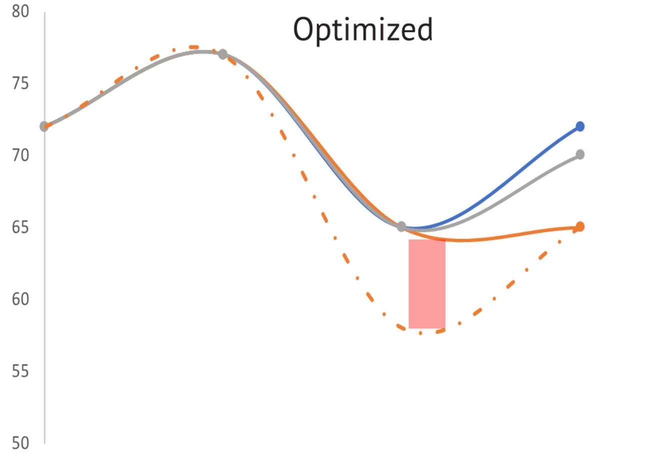
- Goal – To reduce the amount of energy used to control temperature and humidity in art gallery spaces.
  - Criteria
    - ✓Spaces to be maintained at 72+/-4°F and 50% +/-5% RH at all times
    - ✓Approach must be fast acting and adaptable
    - ✓Must not interfere with the existing building automation system
    - ✓Easy to turn off if temperature and humidity are not properly controlled
    - ✓Improve space conditions
    - ✓Save energy




Normal cooling - space humidity is satisfied




Dehumidification - space humidity too high




Represents energy savings potential. Occurs in AIC air handlers 35% to 45% of the time.

# What is this tool?

## Concept Overview

- Can we build **a third-party machine** learning model that will learn from the art institutes air handler and space temperature performance to reduce energy required to cool the space and control the humidity level?
- Can we do this using the existing JCI BAS system while giving the buildings technicians total control when and when not to use the tool?

**Build a Model:** Using a third-party tool from Microsoft Azure toolset. This is the "Model." that sets DAT.

**Send to JCI BAS:** Send the discharge air temp setpoint to the existing JCI system.

**Complete Data Loop:** Send the building performance data back to the model for comparison and evolution.

# Where are the savings?

What does raising the discharge air temperature do?

- Lowers demand on chiller plant= Energy Savings
- Increases the % use of Outdoor Air and/or Return Air= Energy Savings
- Reduces Reheat Needs= Energy Savings

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# Model Requirements

## Model Requirements

- Provide optimized discharge air setpoint value, between 52°F and 70°F, based on conditions
- Meet space temperature and humidity setpoints first, save energy second

## Limitations of Traditional Control Methodologies

- Traditional controls techniques are reactive
- Rules based logic challenging with multiple criteria
- Experienced operators know ideal patterns of control, but programming has limitations

# Machine Learning and Predictive Analytics

## Machine Learning Approach

- ML models ingests a whole data set and determines what will happen based on historical data.
- Recreates human experience for different operating conditions.
- Given current condition data from critical points, what will happen next?
- Predict if zone will stay within satisfactory range if next setpoint is used, limits to changing DAT
- Can use logic after ML model to apply limitations or reductions to changes.
- Over time, can feed new data back into model to enhance model performance.

# ML Model Creation Steps

## Project Steps

- Establish data flow from BAS system to analytics platform
- Identify hardware or sensor issues that affect operations
- Create point mapping for naming consistency
- Create ticketing data flow from door scans as occupancy indicator
- Build individual ML models for each air handler, custom, but with reusable template process

## Model Creation Process

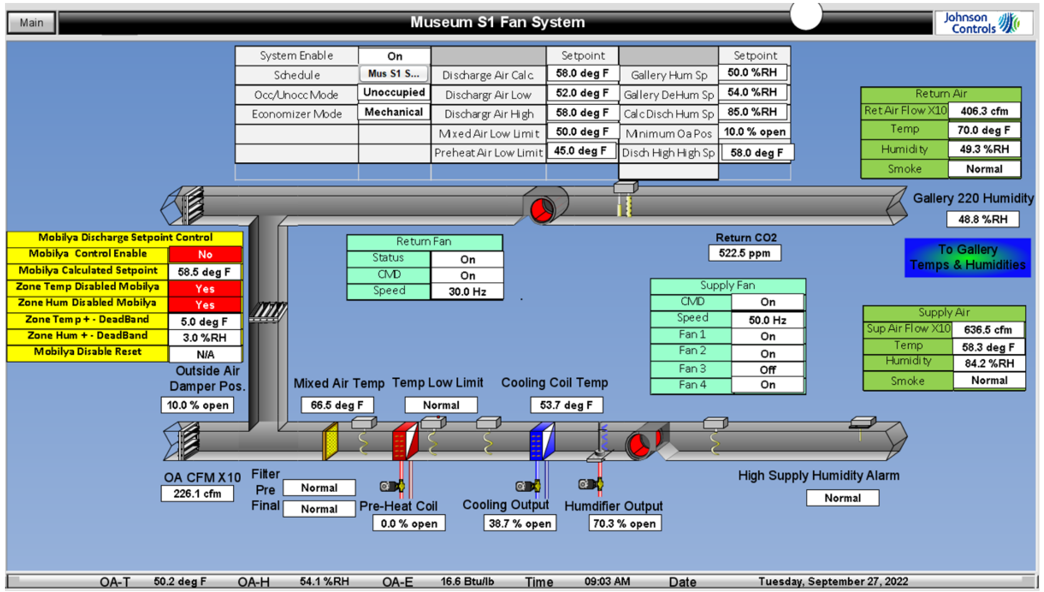
- Provide training data set, identify critical variables
- Develop machine learning model(s), select best characteristics
- Test with new data, known results
- Refine model
- Implement

# Machine Learning – BAS Integration

Create sequence in BAS to utilize optimized setpoint, utilizing limits to ensure space conditions maintained

- Model must meet temperature setpoint, +- 5°F
- Model must maintain humidity setpoint, +-3%
- If limits are exceeded, automatically reverts back to standard setpoint, usually 58F.

| Discharge Setpoint Control | |
|---|---|
| Control Enable | Yes |
| Calculated Setpoint | 64.9 deg F |
| Zone Temp Disabled | No |
| Zone Hum Disabled | No |
| Zone Temp + - DeadBand | 5.0 deg F |
| Zone Hum + - DeadBand | 3.0 %RH |
| Disable Reset | N/A |



# Machine Learning Tech Stack

## Existing (OLD) Building Automation System

- This project is implemented by/on an existing JCI N2 and Pneumatic building automation system.
- Extensive building automation upgrades were NOT required to complete this project.

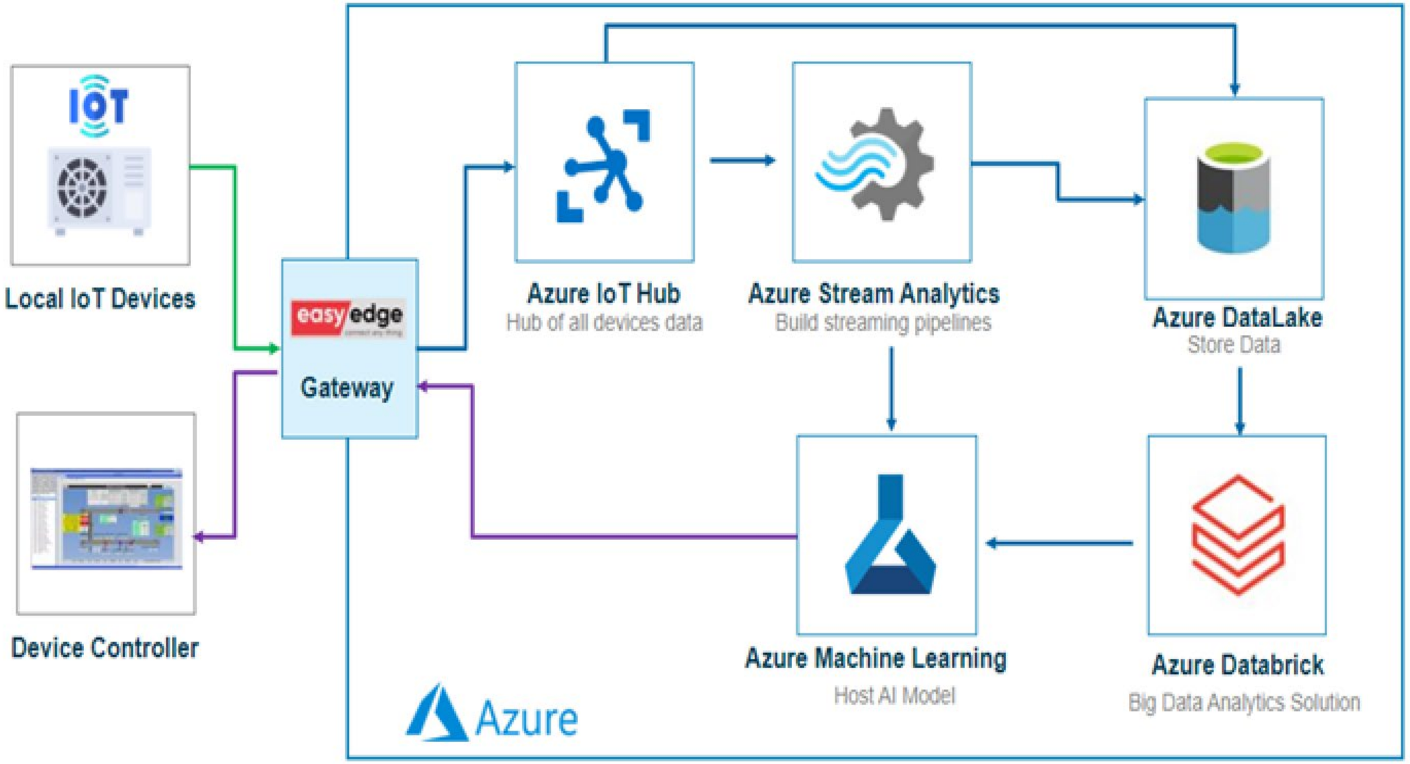
## Consumer Available AI/ML Toolset

- Built with readily available tools.
- Built on the Microsoft Azure ML platform.
- Requires a data connection out and back with the site.

## Project Financials

- Upfront: $500k to implement software, modify existing BAS, build and test programming. Monitor and improve over the first year+.
- Ongoing: Approx.. $1,000 in monthly compute costs, and dropping.
- ROI: Approx.. $220-230k in annual savings. Just over a 2-year simple payback.

# Machine Learning – Data Flow





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  "unit": "ºF"
},
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  "value": "69.875000",
  "unit": "ºF"
},
"realtime::from-N2-A_11A017DX__MUS_S-3_FAN_CHW-S": {
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  "value": "41.625000",
  "unit": "ºF"
```

# So, What Happened?

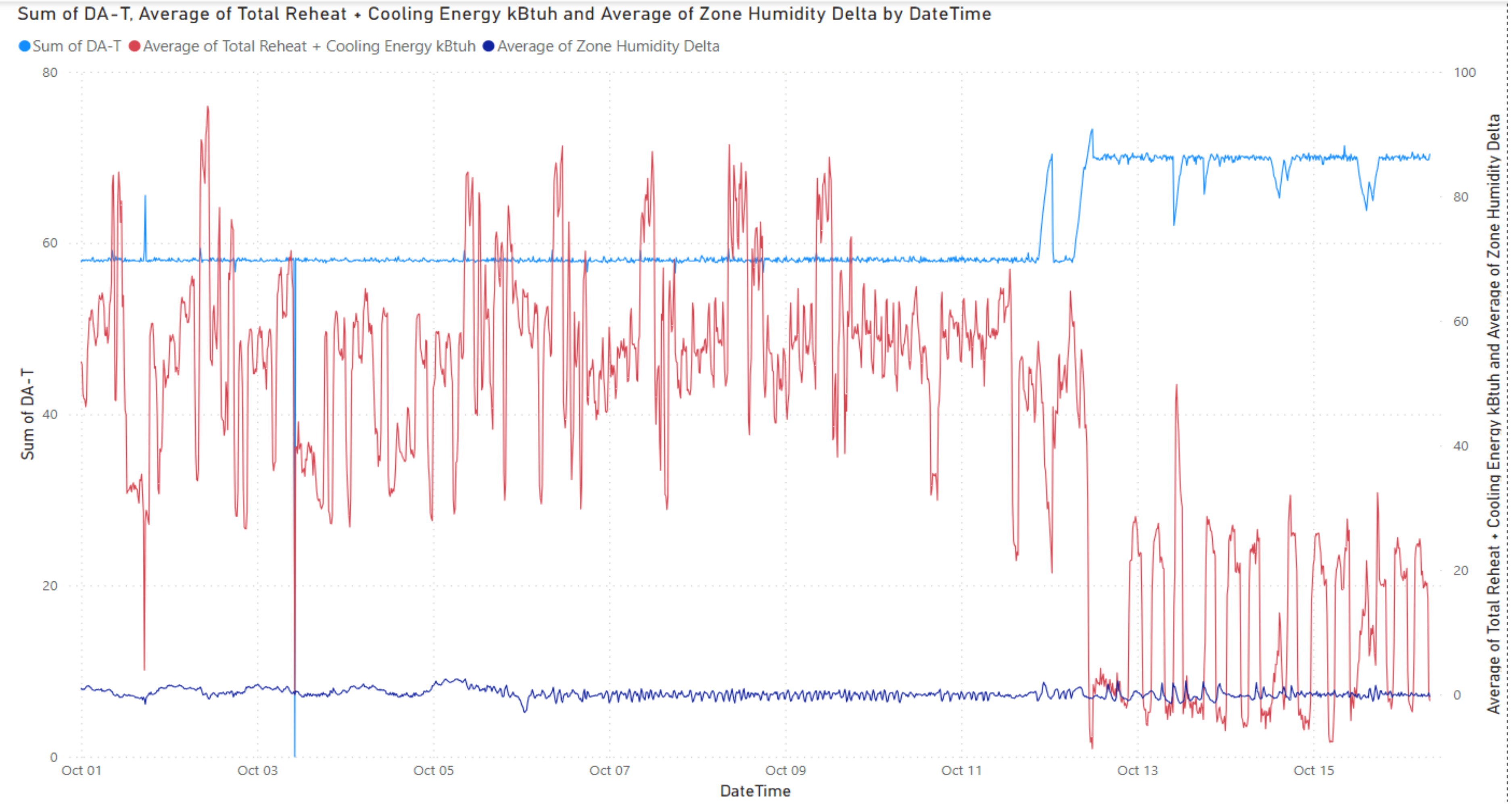
## Deployed on small set of AHUs to Run as a test.

- Used first year of data to input into the model to improve.
- Tweaked the weight of the model's data to:
  - Reduce trips.
  - Increase amount of time the model could run.
  - Improve performance.

## Results

- Energy was/is being saved.
- Deployed to rest of eligible Air Handlers.
- **Space Temperature and Humidity control IMPROVED.**
- As Discharge air temp setpoint went up, reheat need went down.

# Results – Museum S1

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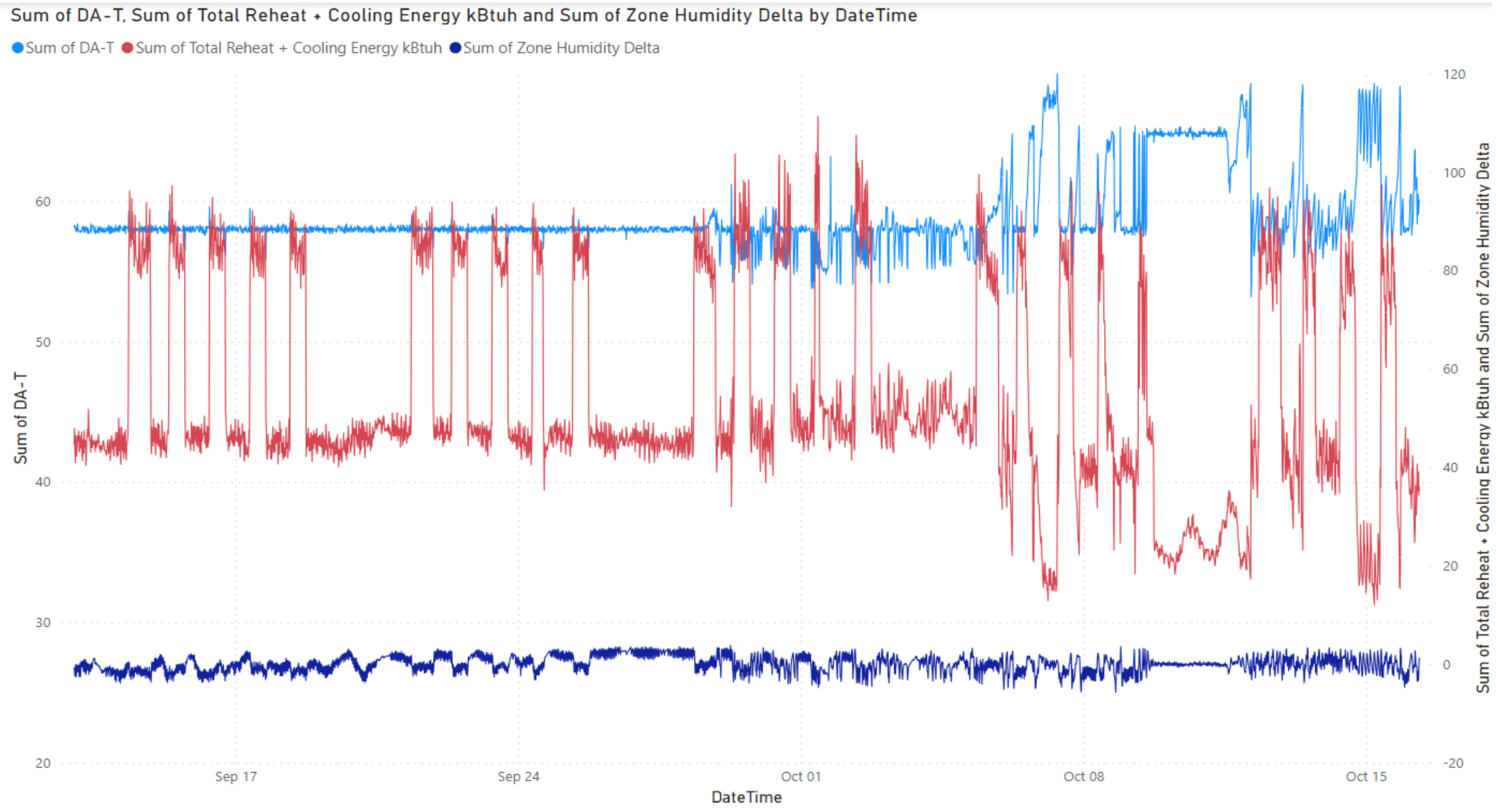
# Results – Museum S2

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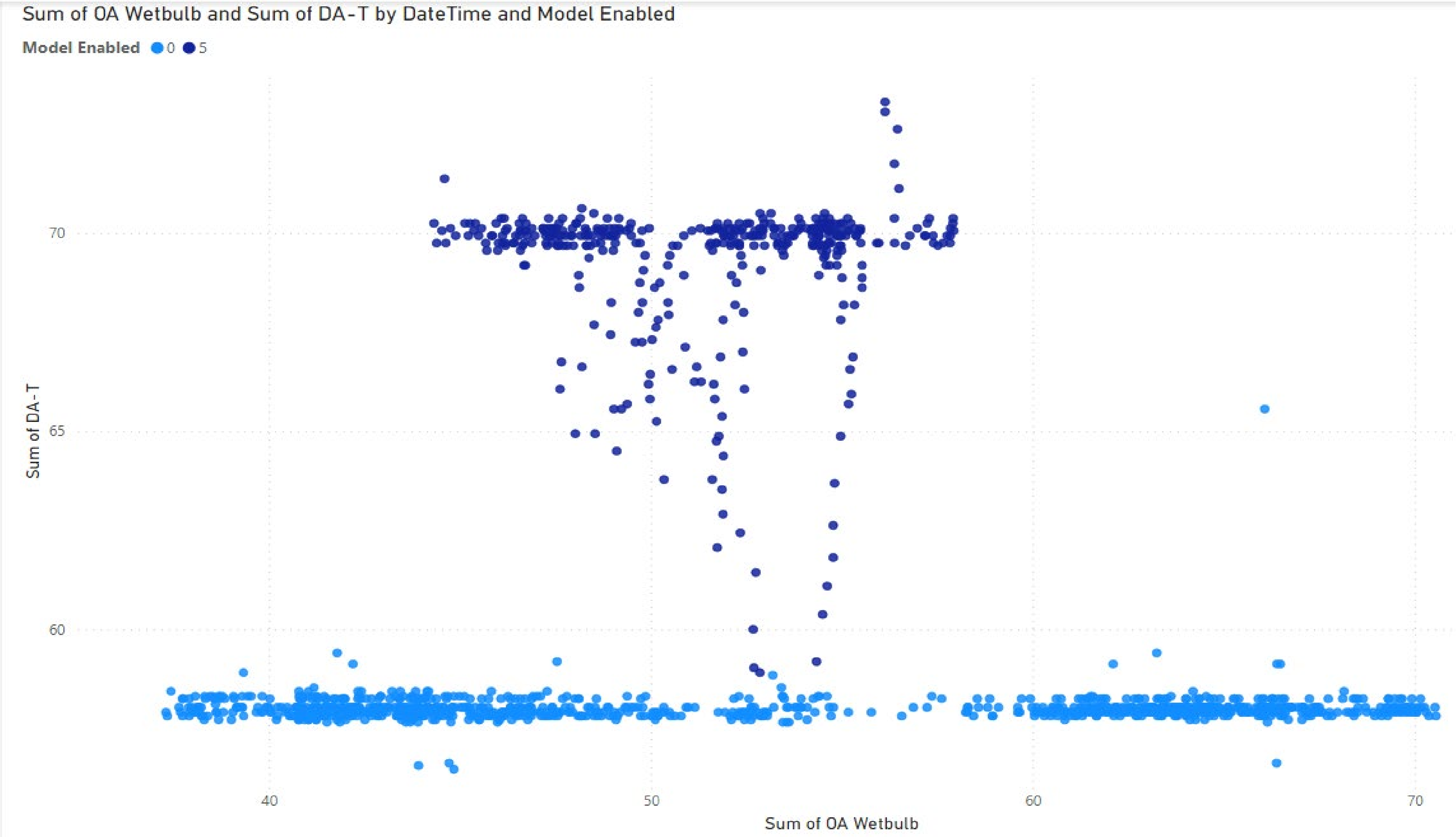
# Results – Museum S1 – OA Wetbulb vs DA-T

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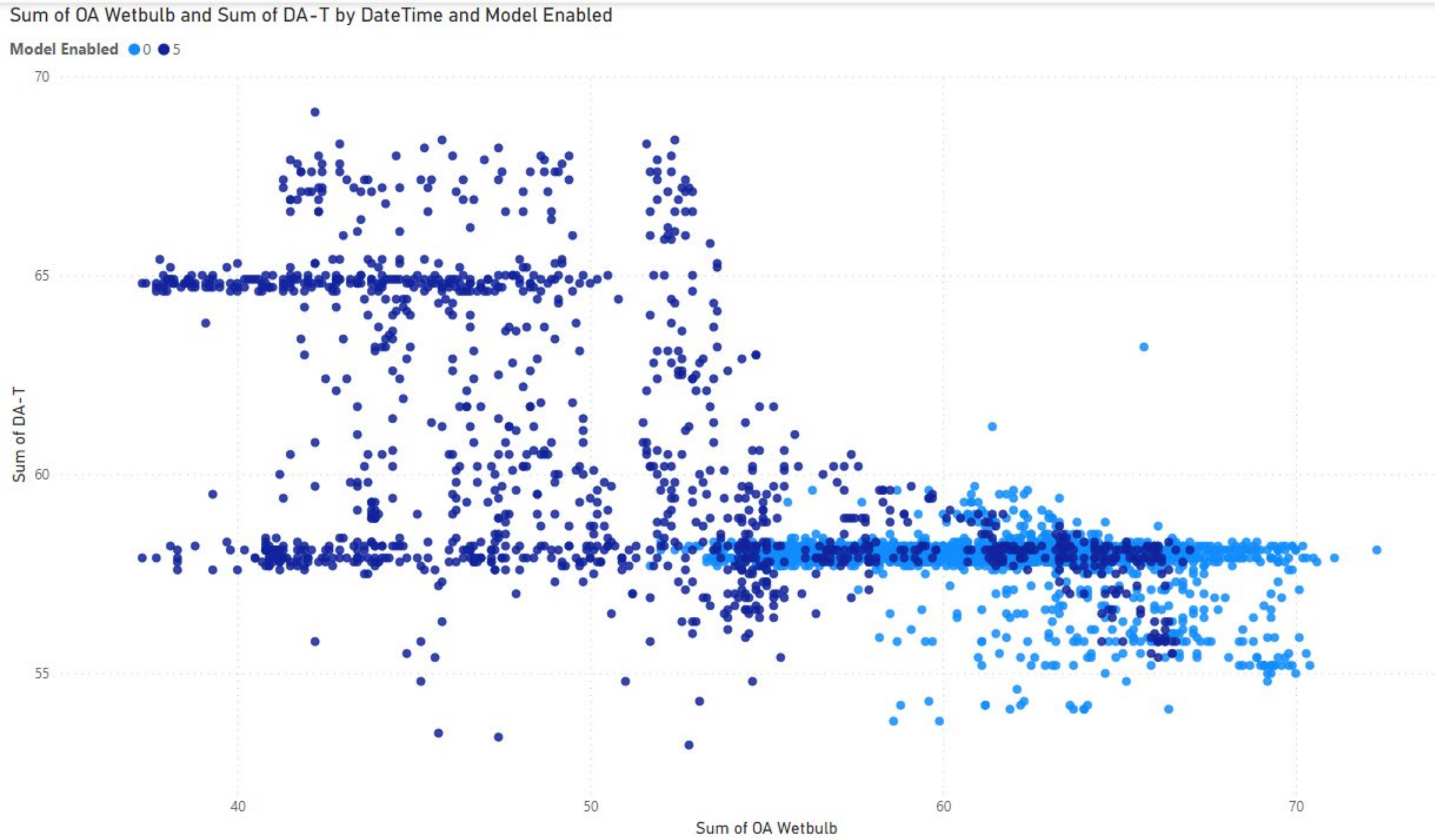
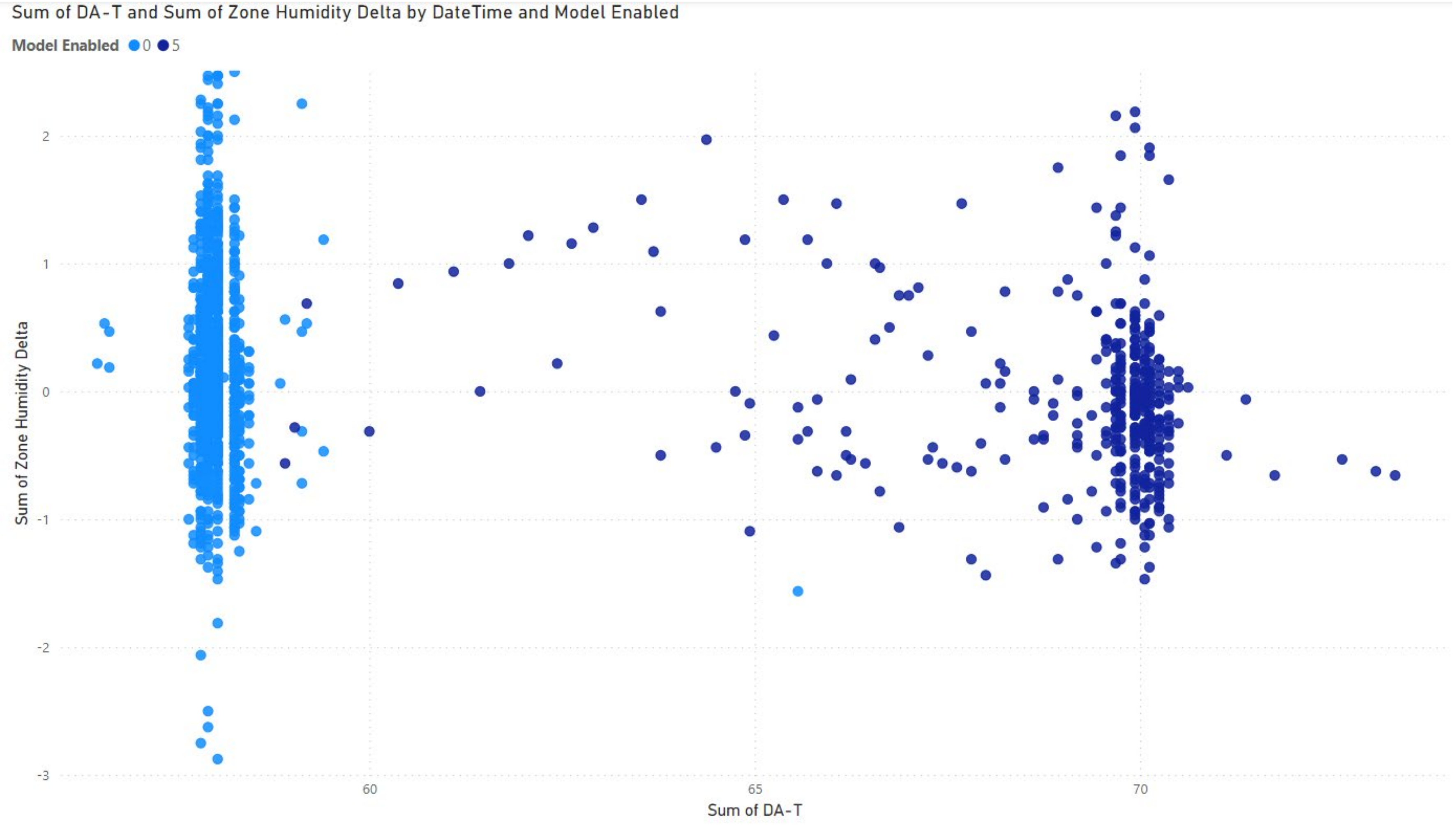
# Results – Museum S2 – OA Wetbulb vs DA-T



# Results – Museum S1 – DAT vs Humidity Delta

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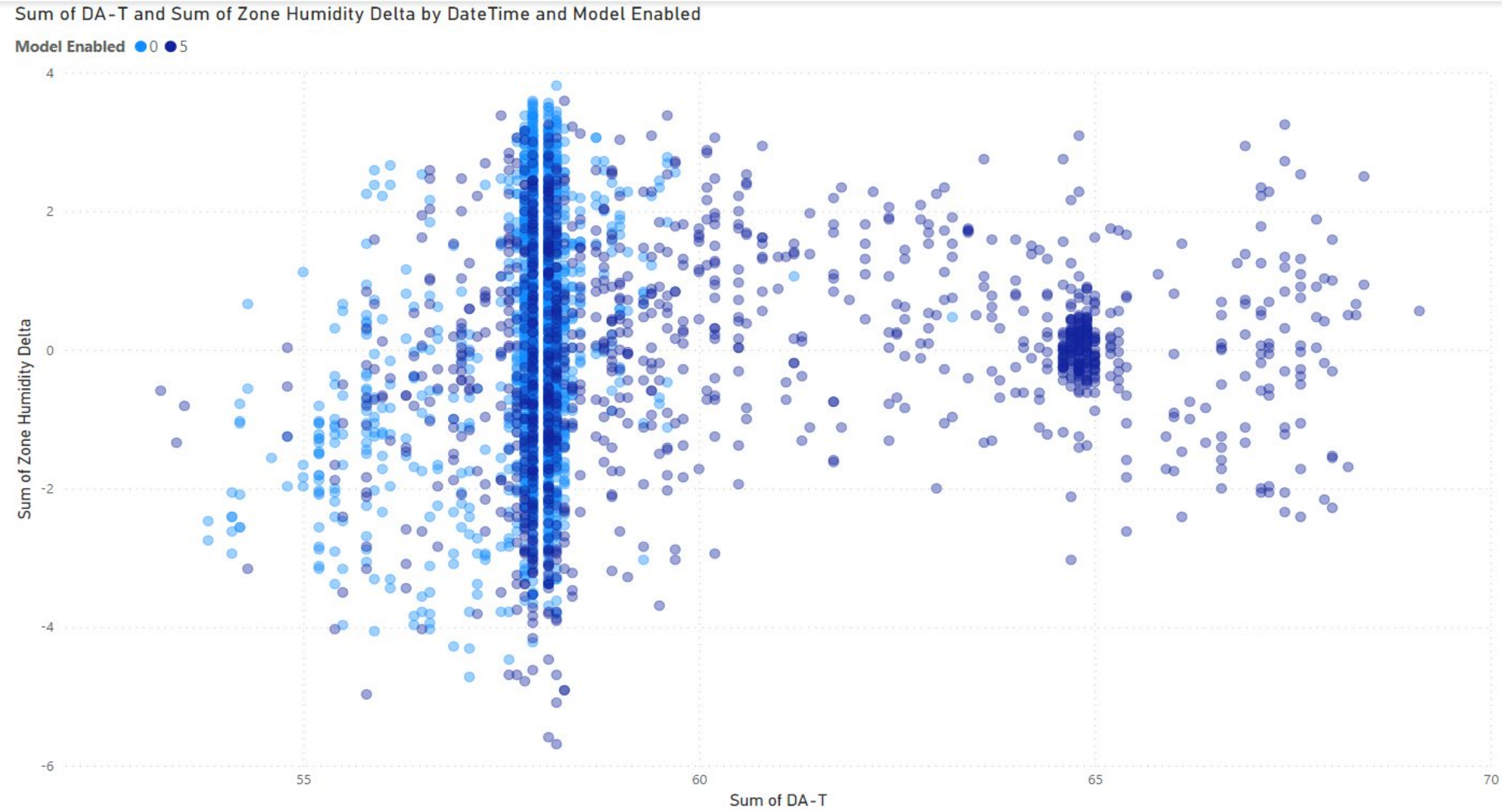
# Results – Museum S2 – DAT vs Humidity Delta

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# Conclusions

1

Significant technology advances make advanced data analytics possible

2

Processing vast quantities of data can be completed quickly

3

Real time analytics of metering data & building automation system data can identify issues & locate opportunities to improve building performance & save energy

4

Bidirectional data flow can be utilized to create more advanced optimization tools for facilities

# Other Applications Ideas

- **What other opportunities exist to utilize ML/AI Today?**
  - **Large buildings with large HVAC equipment (central plants).**
  - **Buildings with high tolerances.**
  - **Buildings with dynamic loads.**
    - **Occupancy changes.**
    - **Intensity of demand on the space.**
  - **Owners/Manager desiring to have buildings perform better.**

# Thanks for wanting to learn more about AI in Buildings!

Discussions/Questions

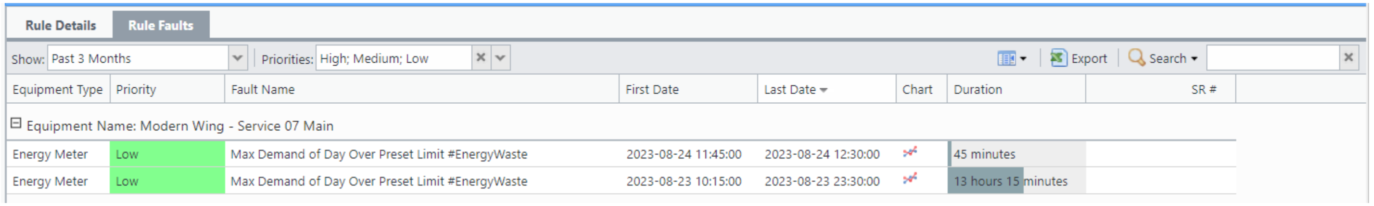
# Appendix

# Long Term Maintenance

- Models are trained with historic data, but periodic retraining will be necessary
- Changes in the building will affect model prediction quality
- Provide critical parameters to operations team, impact of sensor replacement/calibration
- Be mindful of cloud computation costs when designing system, monitor and optimize

# Panel Level Monitoring

- Collecting kW, kWh, Volts, Amps, Power Factor
- Data collected for a period to identify baseline
- Create rules to identify anomalies on major equipment, panels
- Flexible rules, day/night, weather dependent

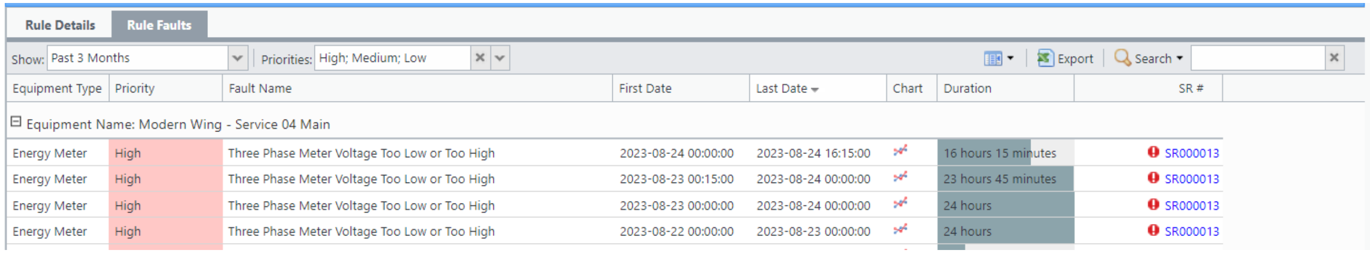


Rule Details | Rule Faults

Show: Past 3 Months | Priorities: High; Medium; Low | Export | Search

Equipment Name: Modern Wing - Service 07 Main

| Equipment Type | Priority | Fault Name | First Date | Last Date | Chart | Duration | SR # |
|---|---|---|---|---|---|---|---|
| Energy Meter | Low | Max Demand of Day Over Preset Limit #EnergyWaste | 2023-08-24 11:45:00 | 2023-08-24 12:30:00 | | 45 minutes | |
| Energy Meter | Low | Max Demand of Day Over Preset Limit #EnergyWaste | 2023-08-23 10:15:00 | 2023-08-23 23:30:00 | | 13 hours 15 minutes | |

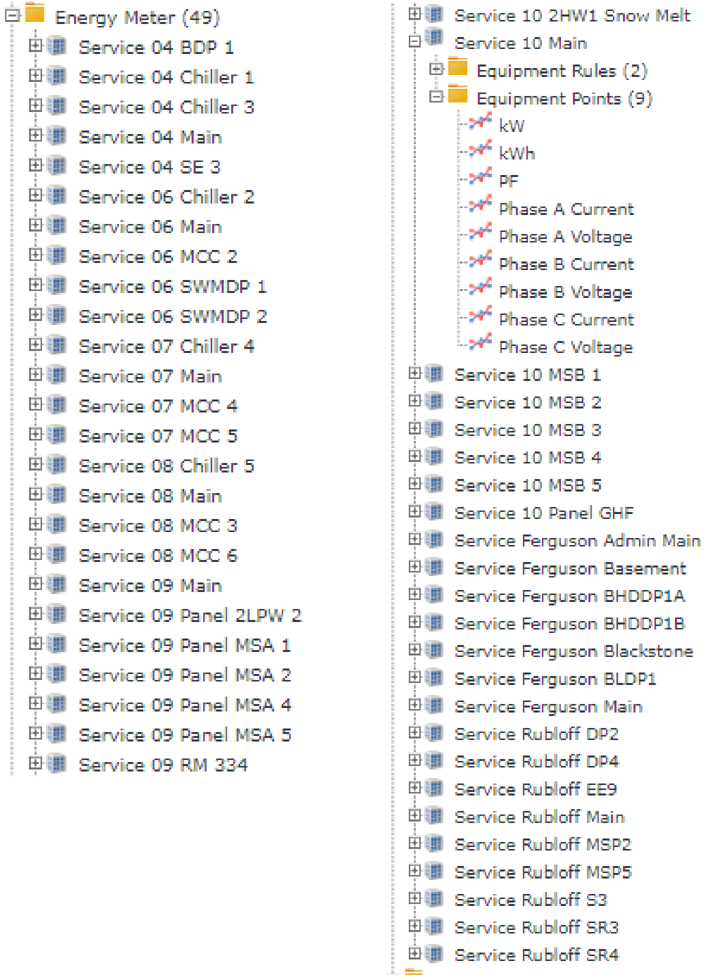


Rule Details | Rule Faults

Show: Past 3 Months | Priorities: High; Medium; Low | Export | Search

Equipment Name: Modern Wing - Service 04 Main

| Equipment Type | Priority | Fault Name | First Date | Last Date | Chart | Duration | SR # |
|---|---|---|---|---|---|---|---|
| Energy Meter | High | Three Phase Meter Voltage Too Low or Too High | 2023-08-24 00:00:00 | 2023-08-24 16:15:00 | | 16 hours 15 minutes | SR000013 |
| Energy Meter | High | Three Phase Meter Voltage Too Low or Too High | 2023-08-23 00:15:00 | 2023-08-24 00:00:00 | | 23 hours 45 minutes | SR000013 |
| Energy Meter | High | Three Phase Meter Voltage Too Low or Too High | 2023-08-23 00:00:00 | 2023-08-24 00:00:00 | | 24 hours | SR000013 |
| Energy Meter | High | Three Phase Meter Voltage Too Low or Too High | 2023-08-22 00:00:00 | 2023-08-23 00:00:00 | | 24 hours | SR000013 |

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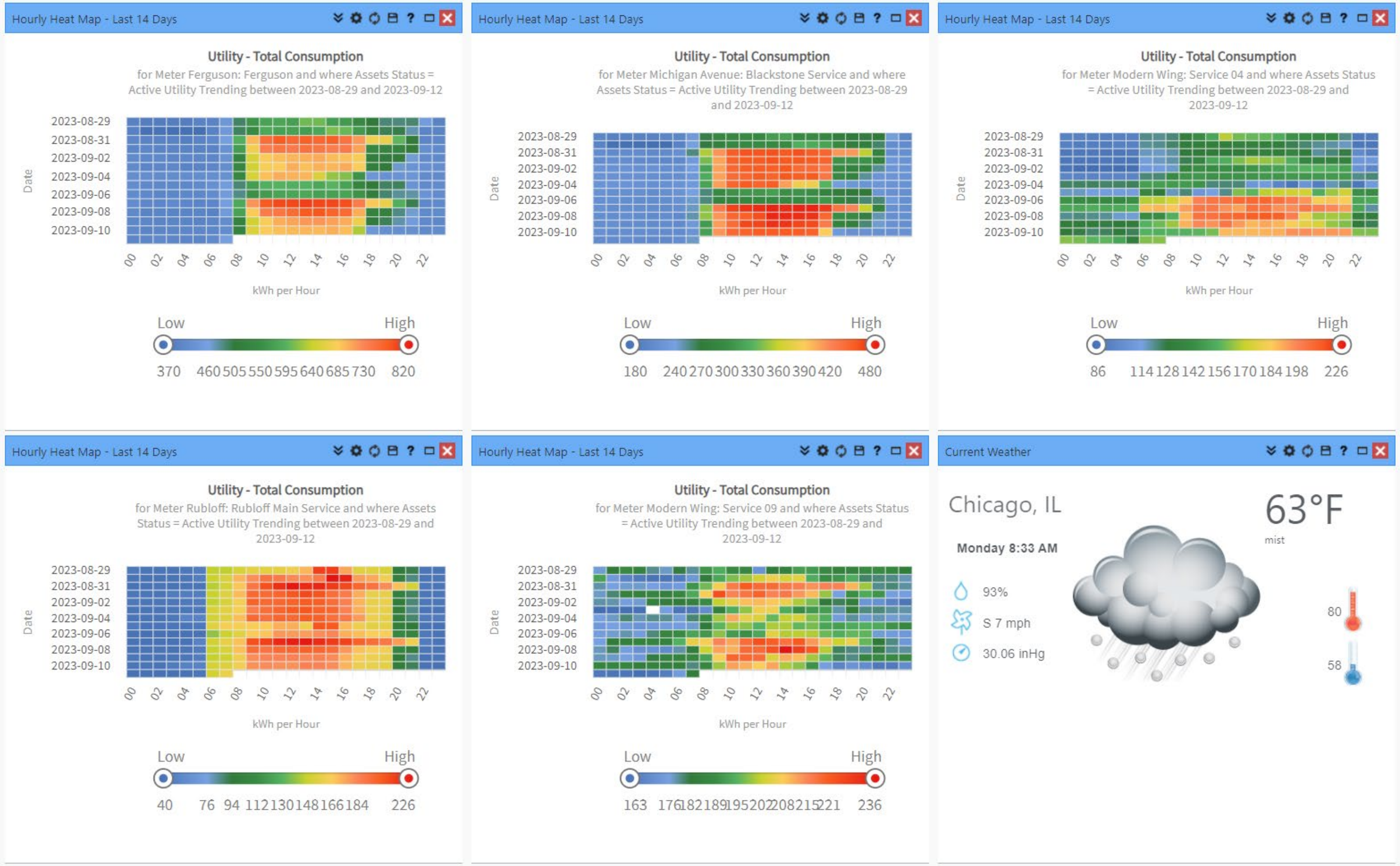
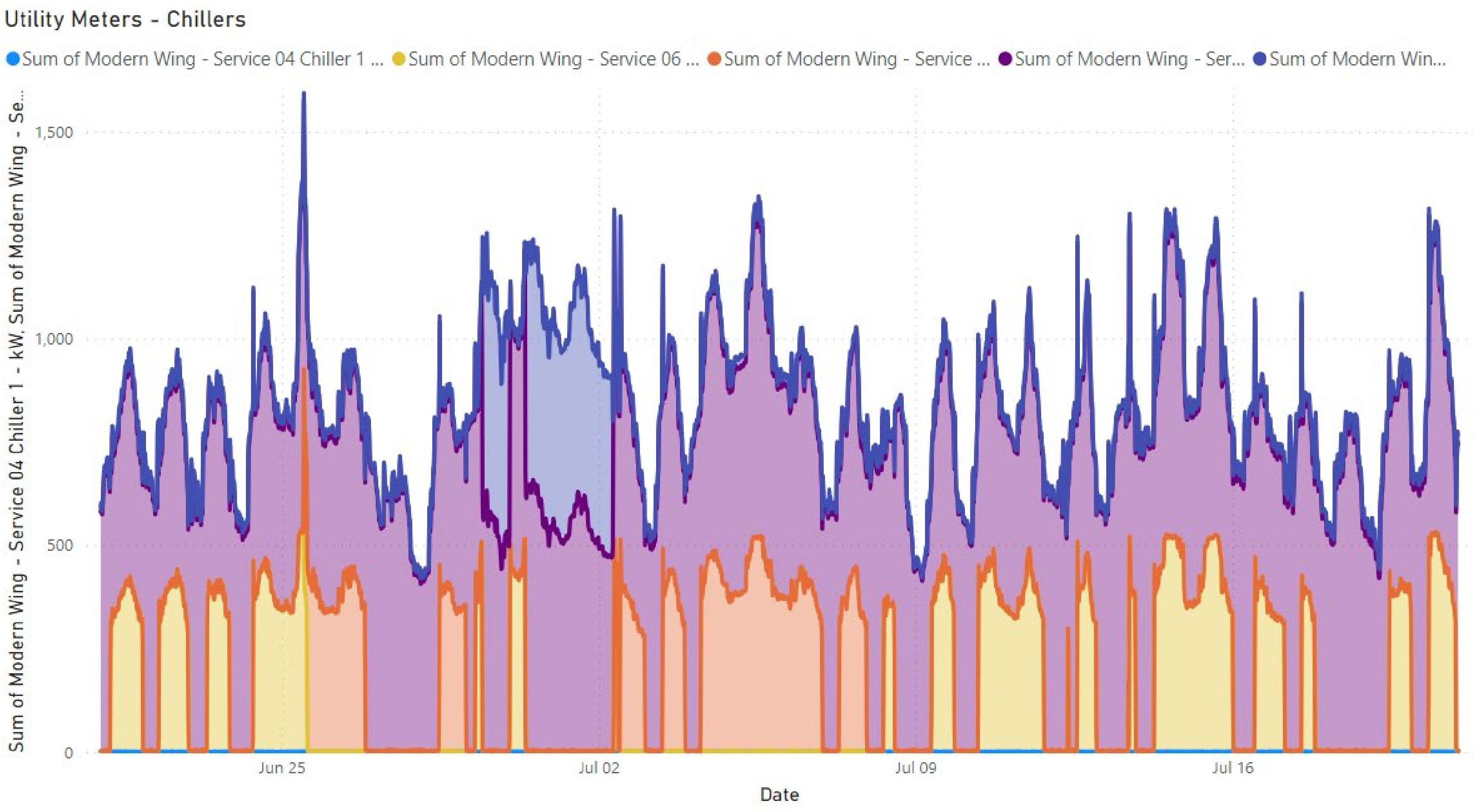
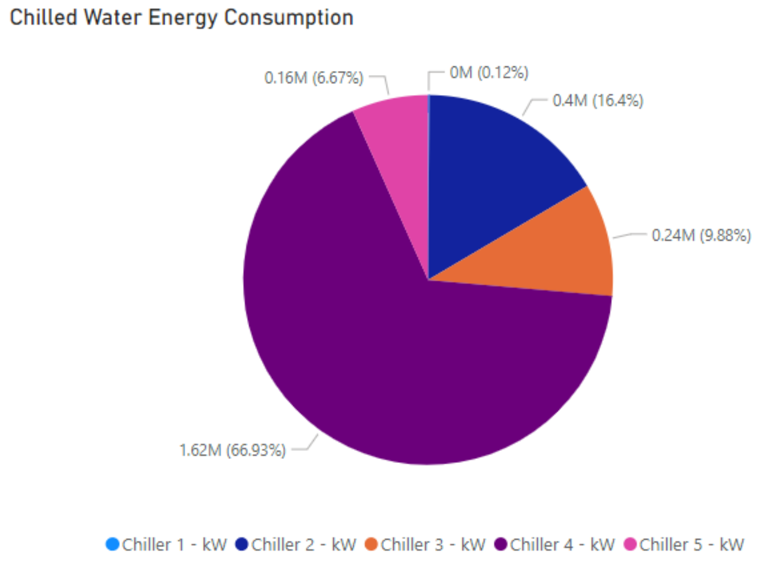
# Panel Level Monitoring Dashboard

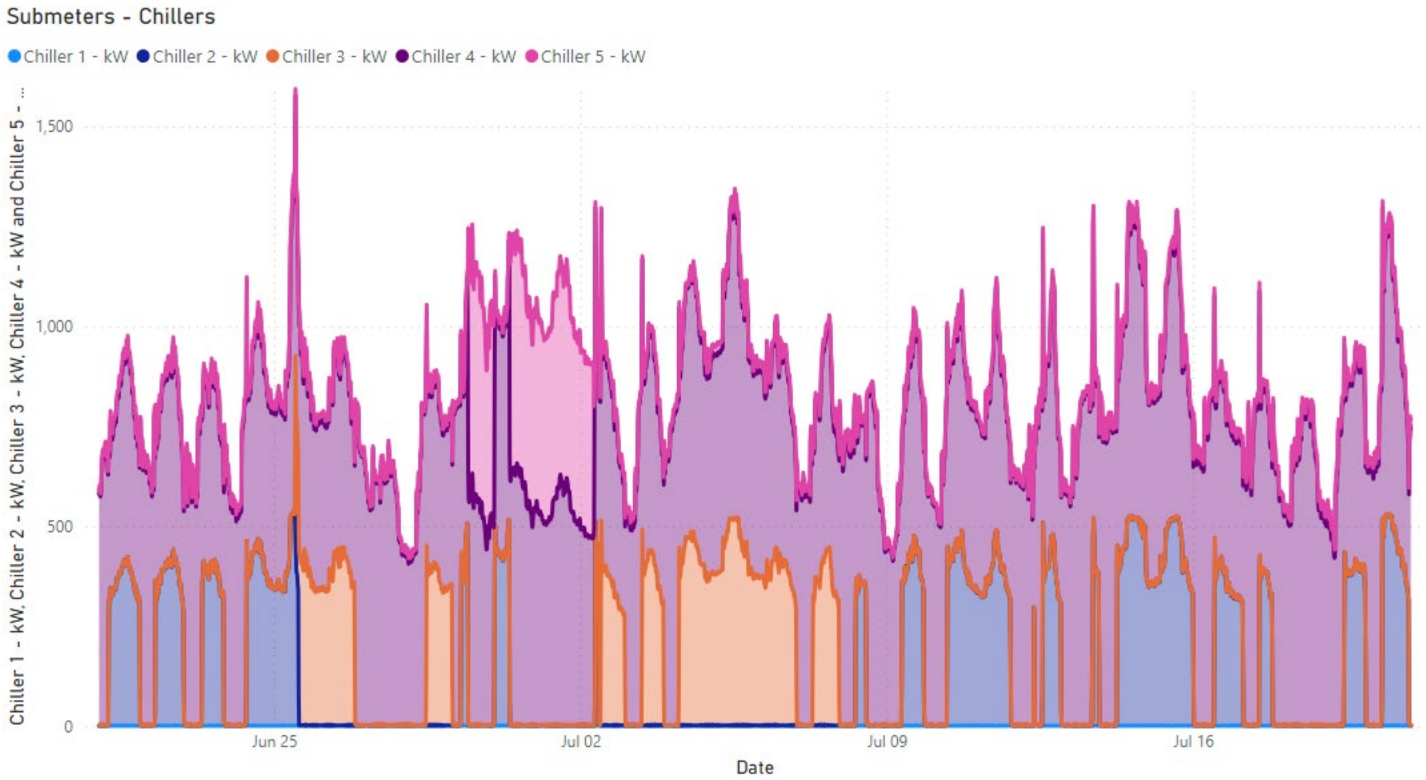


# Campus Metering - Chillers

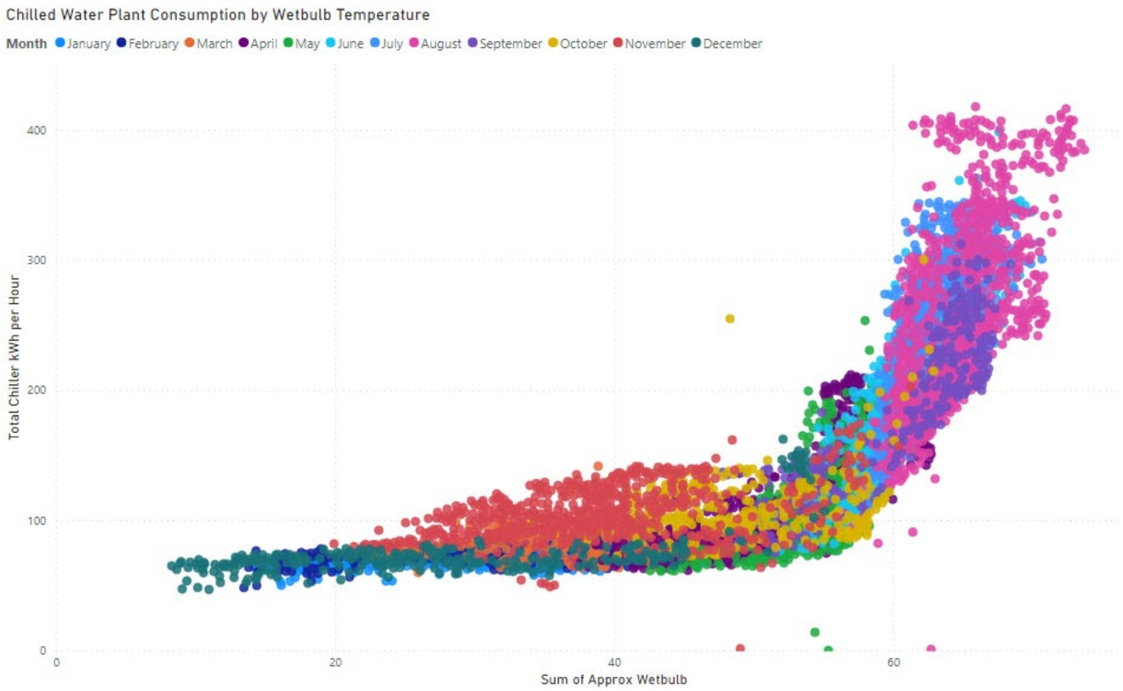


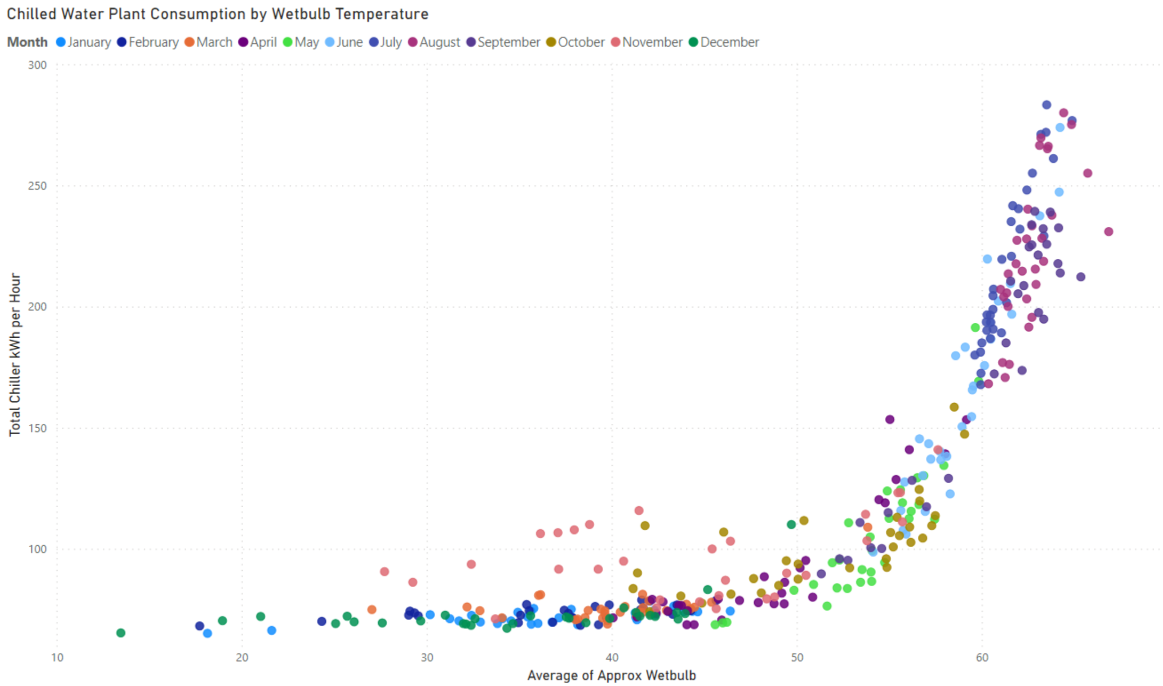
# Chiller Plant Energy Consumption



# Chiller Plant Energy Consumption

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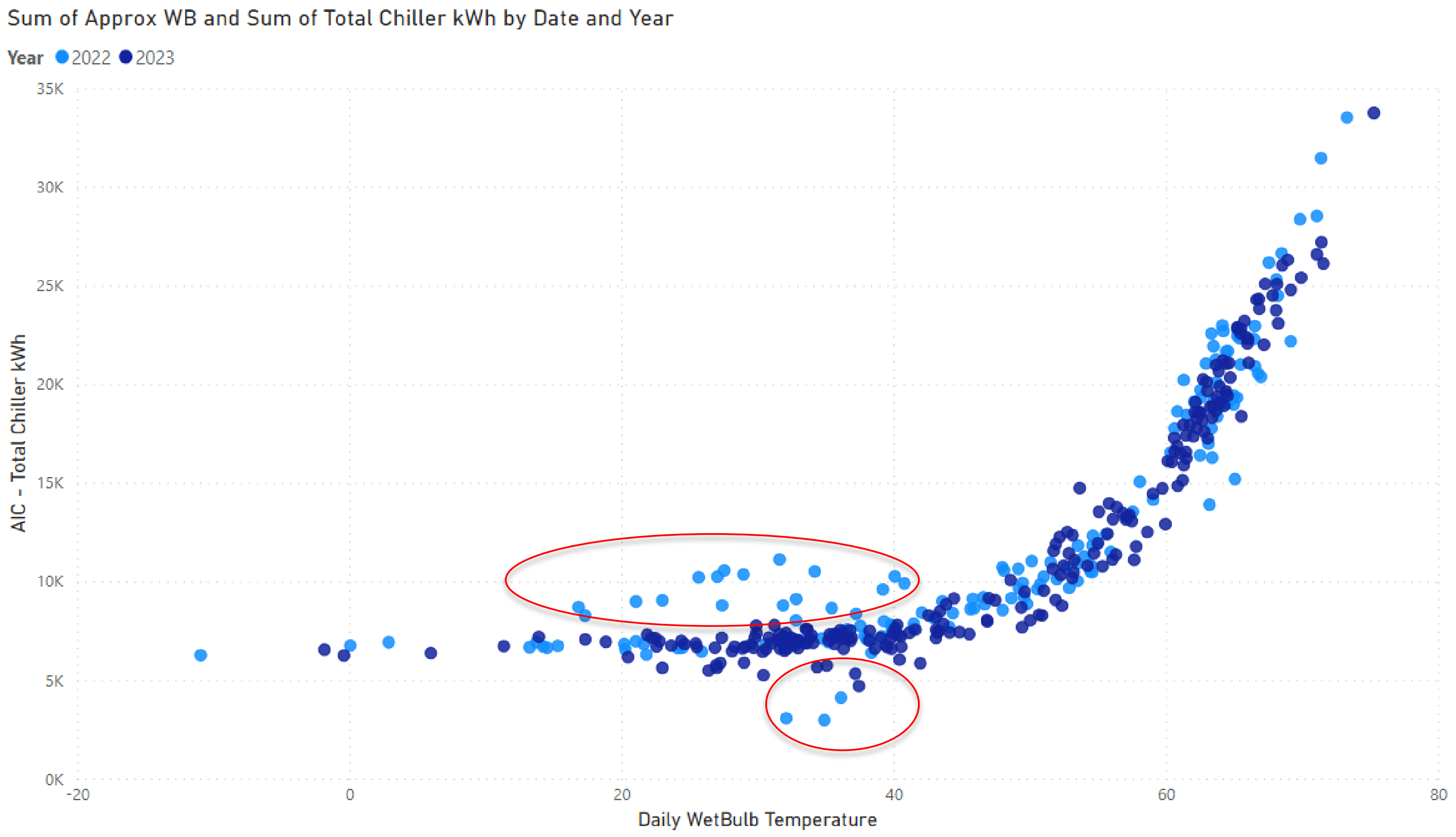
# Chiller Plant Energy Consumption

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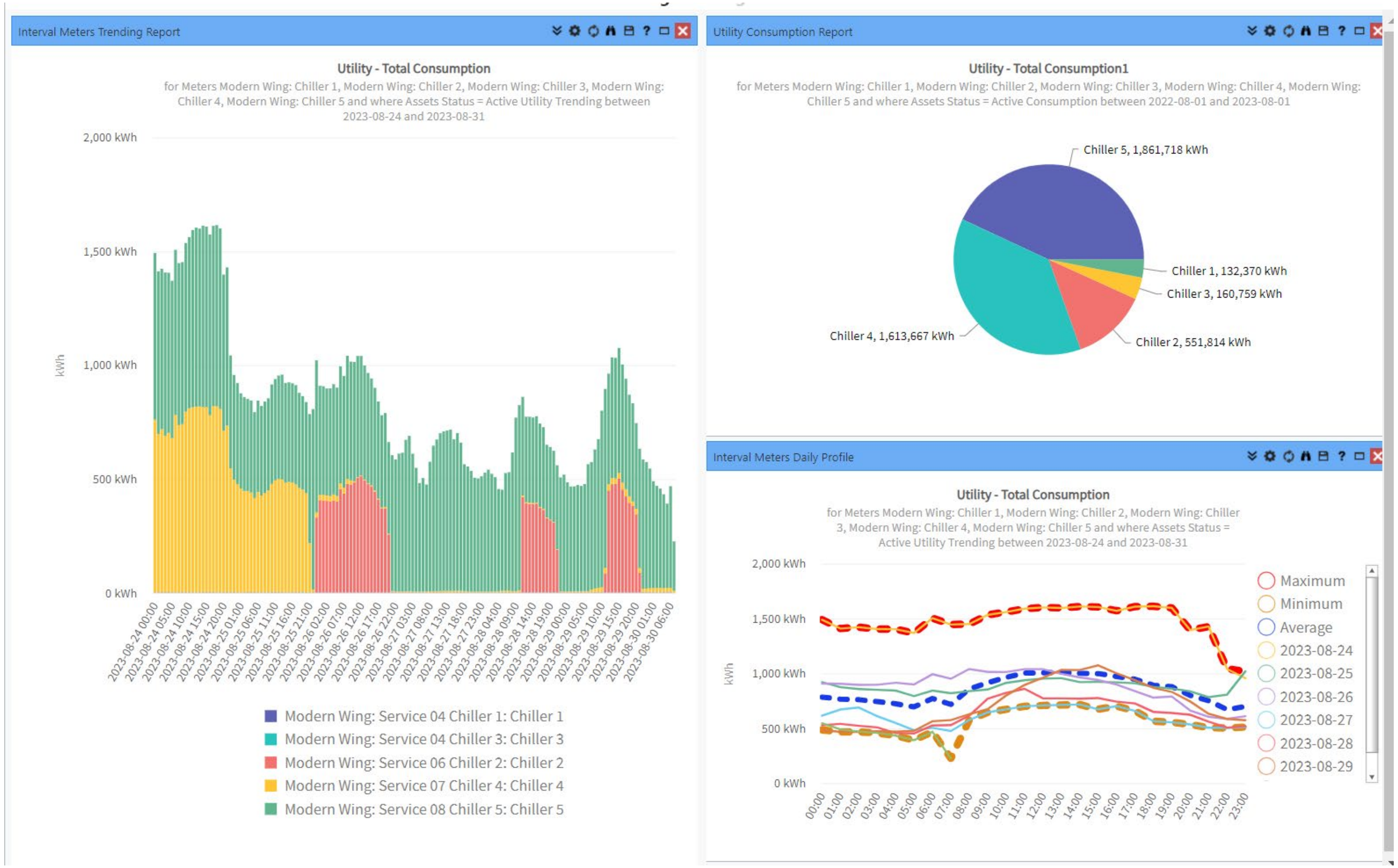
# Chiller Energy Dashboard

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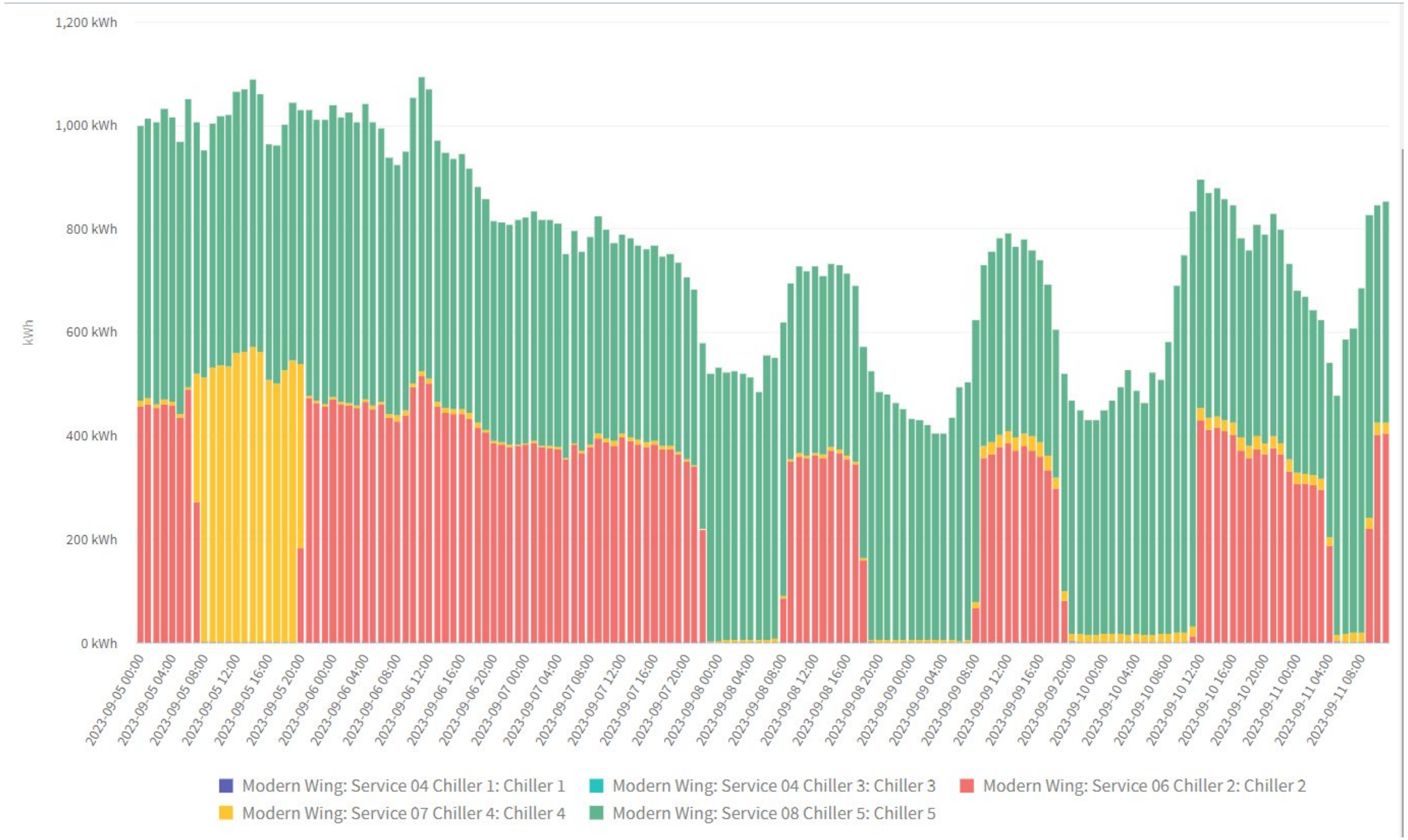
# Chiller Energy Tracking

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