

Using AI/ML to Increase Air Quality, Reduce Costs & Greenhouse Emissions, & Solve Issues

Lucas Dixon & Jarret Kelly, Ameresco

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Our Discussion Goals

- **Introduce Ameresco's experience in Healthcare.**
- **Introduction of a few concepts**
 - **To control costs, achieve compliance, and work toward environmental goals, energy savings is a MUST.**
 - **Previously unachievable energy savings is now achievable with the use of Machine Learning.**
 - **How to deploy tools is varied and changing.**
 - **Building automation is the foundation of using this new tool .**
- **Review Key Machine Learning Example 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.

Proven Experience Working with Healthcare Facilities

- Adventist Health Castle
- Alaska Native Tribal Health Consortium
- Asheville VA Medical Center
- Atlanta VA Medical Center
- Augusta VA Medical Center
- **Banner Health** (multiple sites)
- BC Provincial Health Services Authority
- Beckley VA Medical Center
- Birmingham VA Medical Center
- Boulder Community Hospital
- Boston Children's Hospital
- Brigham and Women's Hospital
- Buffalo Psychiatric Center
- Cambridge VA Clinic CBOC
- Centre Hospitalier Pierre Janet
- Charleston VA Medical Center
- Chillicothe VA Medical Center
- Cincinnati VA Medical Center
- CIUSSS du Nord-de-L'île-de-Montreal
- Clarks Summit State Hospital
- CLSC de Bordeaux-Cartierville
- CLSC de Verdun
- Columbia VA Medical Center
- Columbus VA Medical Center
- **CommonSpirit Health** (multiple sites)
- Community Hospital of Anaconda
- Coventry and Warwickshire Hospitals
- Danville State Hospital
- Dayton VA Medical Center
- Dublin VA Medical Center
- Durham VA Medical Center
- Essex Partnership University NHS Foundation
- Fayetteville VA Medical Center
- Four County Health Center
- Frimley Health NHS Foundation
- Frontenac County Mental Health Services
- Garrett County Memorial Hospital
- Gouverneur Healthcare Services
- Grace Dart Extended Care Centre
- Hampton VA Medical Center
- Harvard Medical School
- Health Care REIT
- Hospital du Sacre-Coeur de Montreal
- Hospital De Papineau
- Jean Mance Hospital
- Jean Talon Hospital
- **Kaiser Permanente** (multiple sites)
- Klickitat Valley Health (Hospital)
- Lee Health - Gulf Coast Medical
- L'Institut de Cardiologie de Montreal
- Logan Health (form. Pondera Medical Center)
- Maine Health
- Marshall Habilitation Center
- Medical University of South Carolina
- Mercer County Hospital
- **Mercy Health Bon Secours** (multiple sites)
- Mercy Health Springfield Medical Center
- Missouri River Medical Center
- Montfort Hospital
- Montgomery VA Medical Center
- Mount Carmel Health System
- Naples Comprehensive Health
- Naples Day Surgery
- National Institutes of Health, UK (multiple sites)
- North Naples Community Hospital
- Newark Beth Israel Medical Center
- Northampton VA Medical Center
- Norton Healthcare
- Nottingham Rehab Ltd
- Omaha VA Medical Center
- Oschner Health
- Pappas Rehabilitation Hospital for Children
- Partners HealthCare
- Pittsburgh VA Medical Center
- Pontiac Hospital
- Richmond VA Medical Center
- RWJ Barnabas Health, Inc.
- Sagamore Children's Psychiatric Center
- Salem VA Medical Center
- Salisbury VA Medical Center
- Scarborough Hospital
- Scioto County MRDD
- Shriners Children's Hospital Honolulu
- Spire Healthcare
- State of New York, Office of Mental Health
- **Sutter Health** (multiple sites)
- Tewksbury Hospital
- The Queen's Health Systems
- Trinitas Regional Medical Center
- Tuscaloosa VA Medical Center
- UnitedHealth Group
- University Medical Center of Southern Nevada
- University of Cincinnati Medical Center
- University of Kentucky Medical Center
- University of Texas MD Anderson Cancer Center
- University of Toledo Medical Center
- US Army Medical Command (MEDCOM) - Fort Eustis, Fort Lee, and Fort Story
- Washington State DCYF
- Washington State Dept. of Veterans Affairs - Walla Walla Skilled Nursing Center; Washington Soldier's Home
- Washington State DSHS (multiple sites)
- Western State Hospital
- Wyandot MRDD

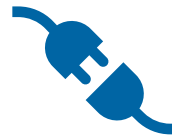
U.S. Healthcare GHG Emissions

- Healthcare accounts for approximately 8.5% of the carbon dioxide emitted annually in the U.S.
- Inpatient healthcare is ranked by EPA as the **second-largest commercial energy user in the United States**.
- One major healthcare system reported 94% of their Scope 1 & 2 emissions were due to energy.
- Energy Utility costs are rising due to increased demand on grid and lack of supply investment.



Scope 1: Direct Emissions

Direct emissions from operations.
Occur from sources that are controlled or owned by the healthcare facility.



Scope 2: Indirect Emissions

Indirect emissions from purchased energy (electric, gas, and other utilities paid for by healthcare facility).



Scope 3: Indirect Emissions

Indirect emissions (not included in Scope 2) that occur in the value chain, including both upstream and downstream emissions (e.g., manufacturing and shipping medical supplies, patients traveling to and from facilities).

Kaiser Permanente

2012 - Present

ALL PROJECTS	KW	# of Sites
Pre-Development	16,167.7	38
Development	5,624.2	10
In Construction	14,287.2	17
Complete	36,897.0	71
Total	72,976.1	136

- 3.58 MW of Battery Energy Storage Systems (BESS) at nine sites.
- **Dedicated staff, ramping up to over 25 team members at the account's peak.**
- Our flexible construction management approach has also accommodated various phases of design, engineering and installation of over 20 locations concurrently.



PARKING GARAGE SUPERSTRUCTURE



SHADE CANOPY



CARPORTS



SUPERSTRUCTURE + CARPORTS



ROOFTOP + CARPORTS



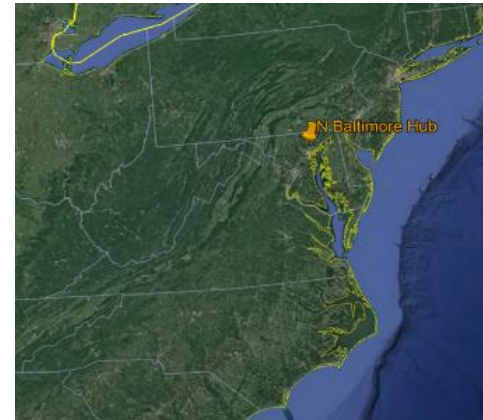
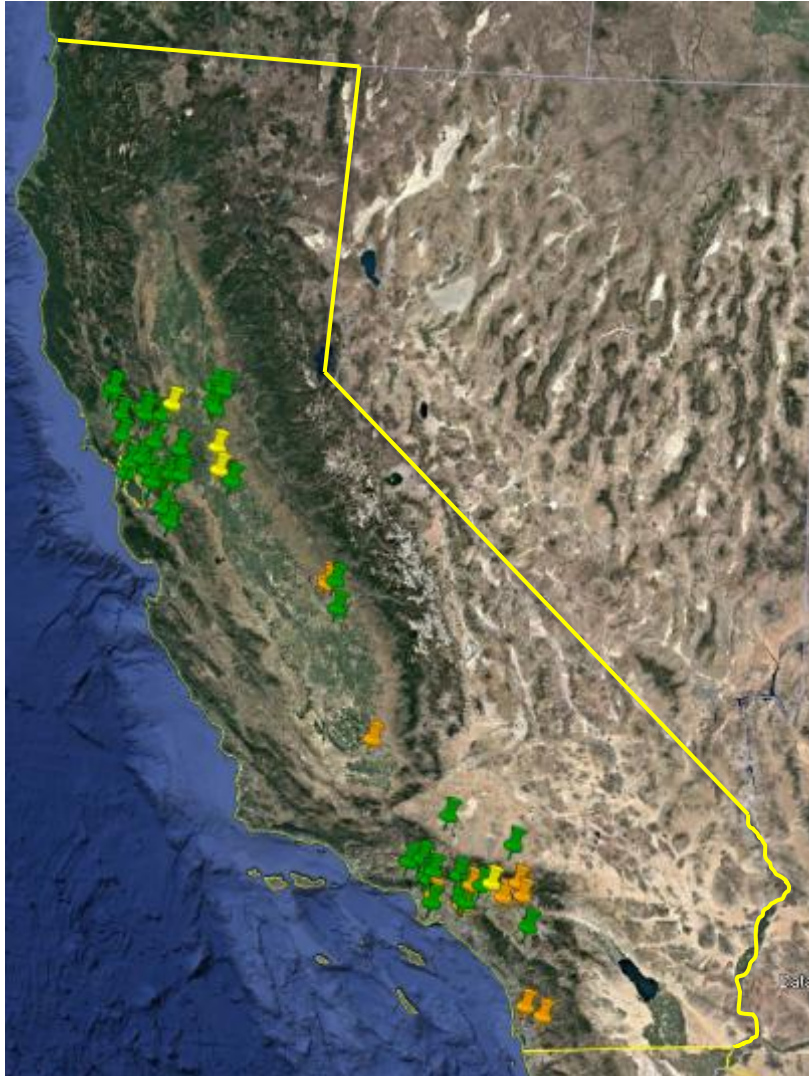
MOB CARPORTS WITH BESS



HOSPITAL CARPORTS



Address Other Aspects of Sustainability: Kaiser Permanente

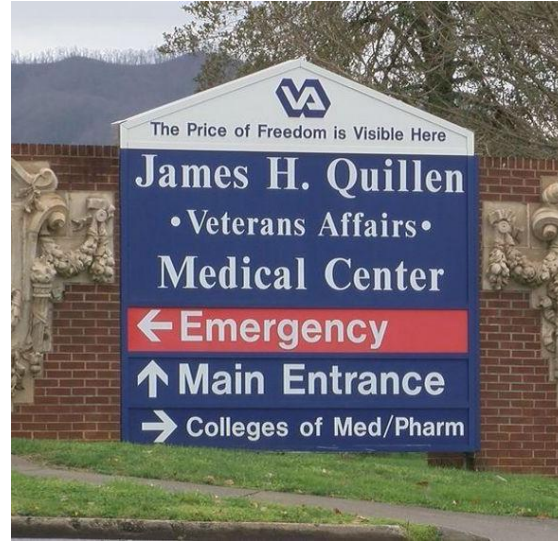


Project Highlights:

- **Enterprise Account:** California, Hawaii & Maryland
- **Solar and Microgrid:** Carport, Superstructure, Ground Mount & Rooftop Installations
- **Portfolio Management:** Staffing for Enterprise Account, Project Controller, Dedicated Engineering and Construction Team, 20+ Locations Concurrent Peak

85 Active/Completed Sites
32 Sites in Development

Case Study: VA Health System UKMC & UTMC



Ameresco is a preferred controls vendor at many sites across the region due to the deep dedication of our team members to working within the constraints of the medical environment to support renovations, new construction, and service support.

System Highlights:

- **Control Technology Types:**
 - University of Kentucky: Niagara Tridium with Distech Terminal Equipment Controllers
 - VA Health System: Computrols front end with Reliable, JCI, and others below.
 - UT MC: Integration of multiple systems using Computrols and Reliable Controls.

Case Study: Naples Community Hospital



Project Highlights:

- **Technology Types:** Design-Build Energy Efficiency
- **Energy Project Size:** \$38,000,000
- **Annual Gas Savings:** \$410,000
- **Annual O&M Savings:** \$325,000

NCH partnered with Ameresco to assemble and implement an Energy Master Plan (Energy Vision 2020) that identified over \$2M in annual savings.

“Ameresco is true to their name. Their deep working knowledge of every type of energy system helped our hospital approach our energy problems intelligently, so that we could better focus on serving our patients. Through their Energy Master Plan, we are saving more than enough money to pay for the project. Most impressively, the team took the time to understand our concerns and our constraints so that we were comfortable. Now our buildings will perform as well as our hospitals have for years.”

—Lee Wehr
Director of Engineering
Naples Community Hospital

Case Study:

Boston Children's Hospital



Children's Hospital Boston and Ameresco partnered in a multi-year agreement to prepare the hospital for their energy future by implementing intelligent energy services.

Project Highlights:

- **Technology Types:** Demand Side Management, Design-Build, Energy Analytics, Energy Efficiency
- **Annual Water Savings:** 12M gallons
- **Energy Project Size:** \$5,600,000
- **Annual Energy Savings:** 9.6M kWh
- **Annual Energy Savings:** \$1,514,120

Starting Point

- Energy savings opportunities are everywhere, but achieving and sustaining them is very difficult.
- 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.
 - Currently building automation systems data is underutilized in large enterprises.

Actions/To Do

- Evaluate the buildings, projects, and operations in your “sphere of influence” with a different lense.
- Keep an open ear, eye, and mind for opportunities to better use your building automation system and be ready to use AI tools.
- 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 implementation to save energy today.**

Application Ideas

- **What opportunities exist to utilize ML/AI Today?**
 - **Heating & Cooling Plant Optimization (HHW/CW Setpoint, Variable Speed Pumping, Predictive Weather)**
 - **AHU Controls for Surgical & Patient Spaces (RH%, Static Pressure Reset)**
 - **Areas with dynamic loads.**
 - **Occupancy, ACH changes.**
 - **Intensity of demand on the space.**
 - **Owners/Manager desiring to have buildings perform better.**

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

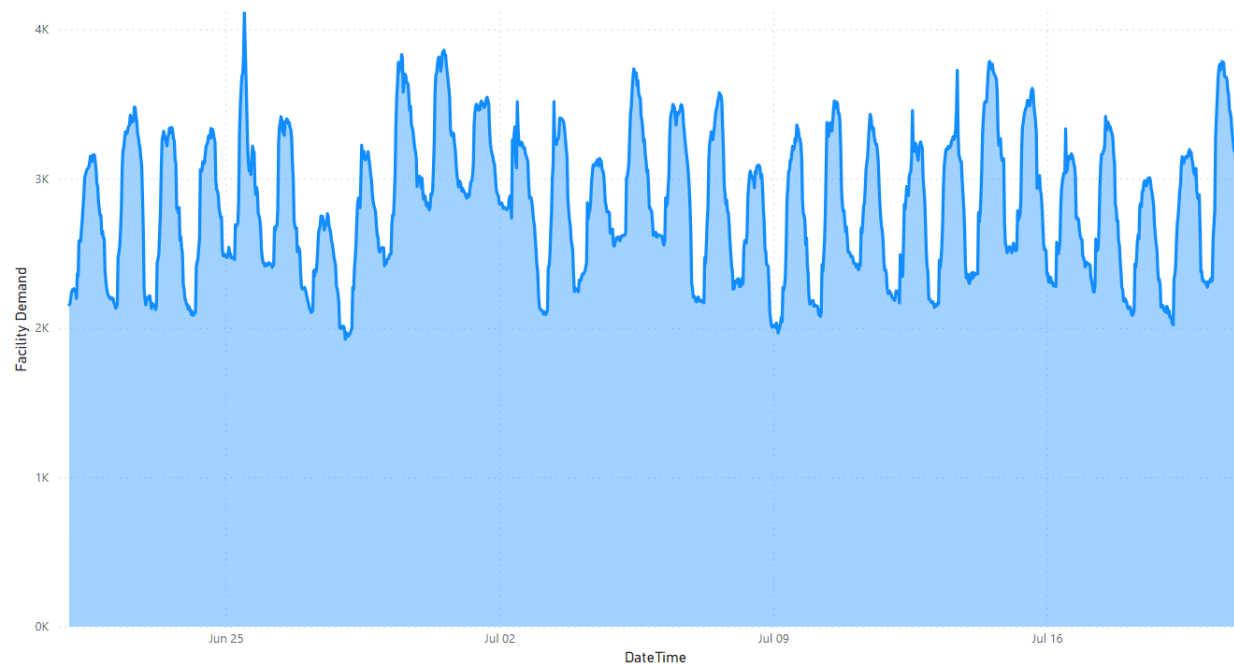


Campus Electrical Metering Project

Overall Metering

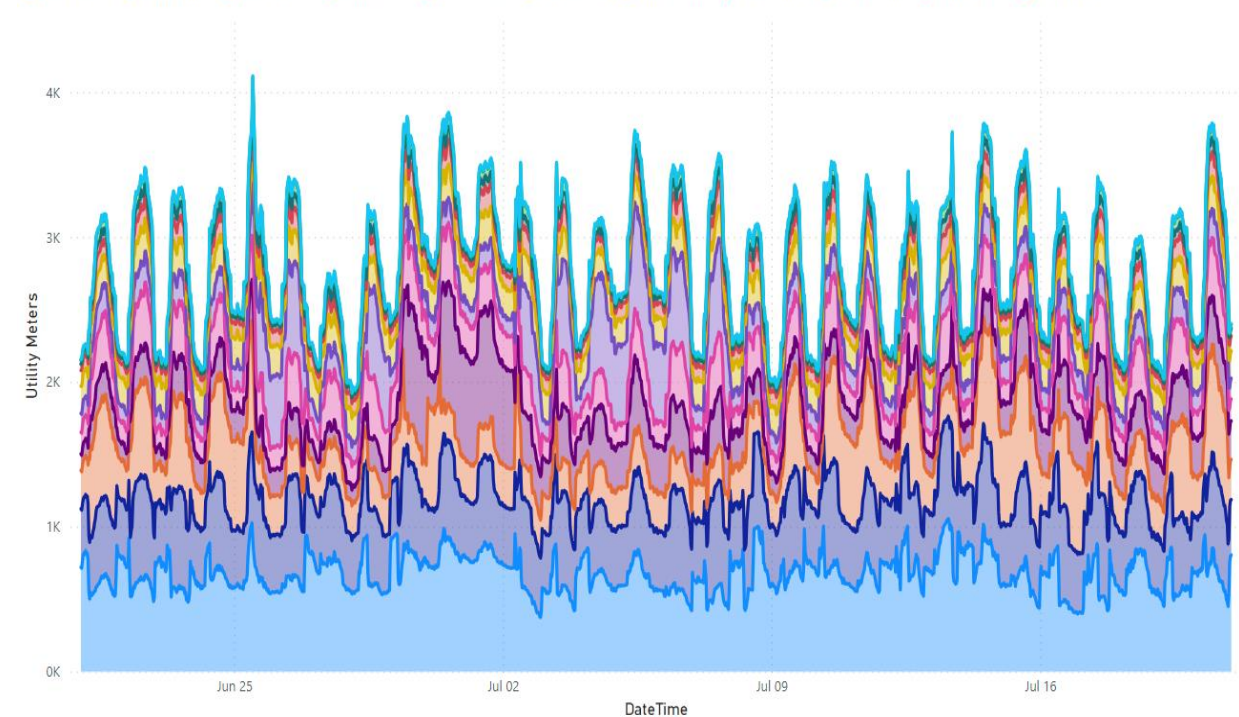
- Sixteen meters located on the campus, 10 with routine usage

Art Institute of Chicago - Overall kW



Campus Energy Consumption - All Utility Meters

● 230197246-1 ● 230077748-1 ● 230197201-1 ● 230197265-1 ● 230197263-1 ● 230197198-1 ● 230197247-1 ● 230197249-1 ● 230197248-1 ● 230197199-1 ● 230169955-1

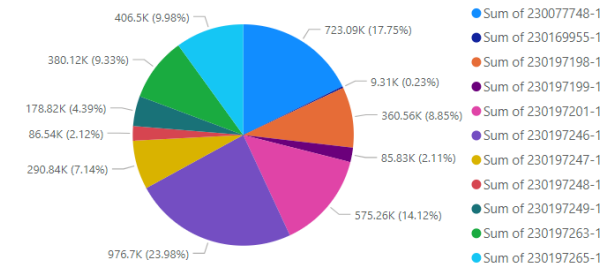


Energy Meter Analysis

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

Utility Meter Loads - July 2023



Meter	Meter Room	Jul 2021		Min kW	Average kW	Daytime Average	Nighttime Average	Load Percentage
		kWh	Max kW					
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%

Summer

Meter	Meter Room	Dec 2021		Min kW	Average kW	Daytime Average	Nighttime Average	Load Percentage
		kWh	Max kW					
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%

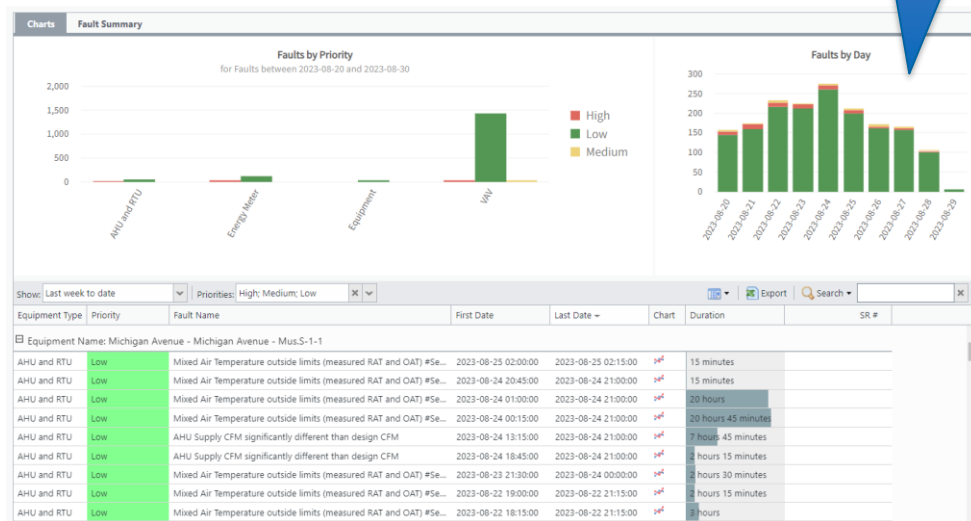
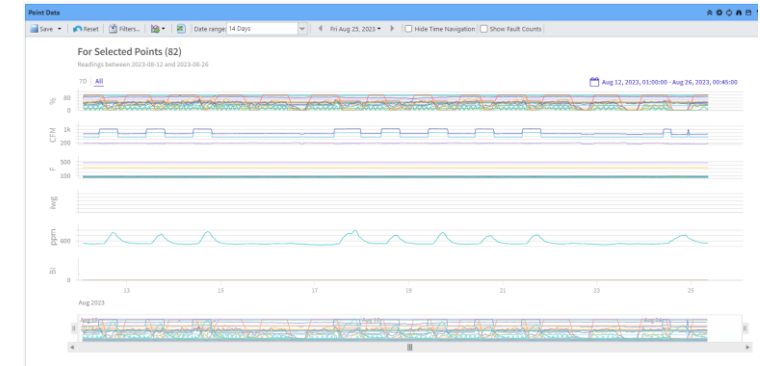
Winter

Building Automation System Analysis



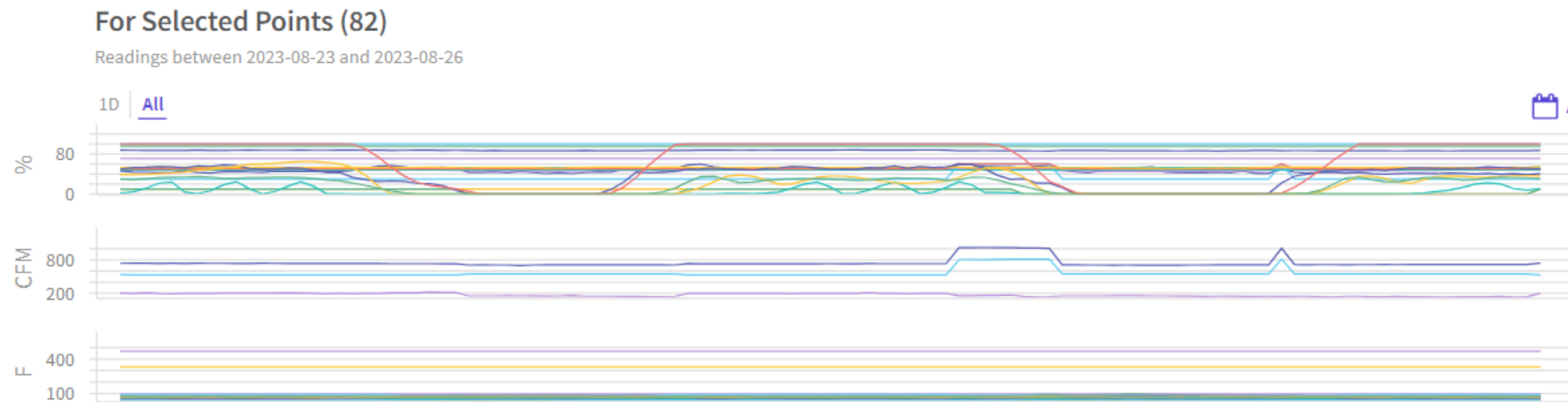
Building Automation System Analysis

- Integration with campus Building Automation System
- Providing cloud-based data analytics
- Rules and configured to monitor
- Proactive identification of energy

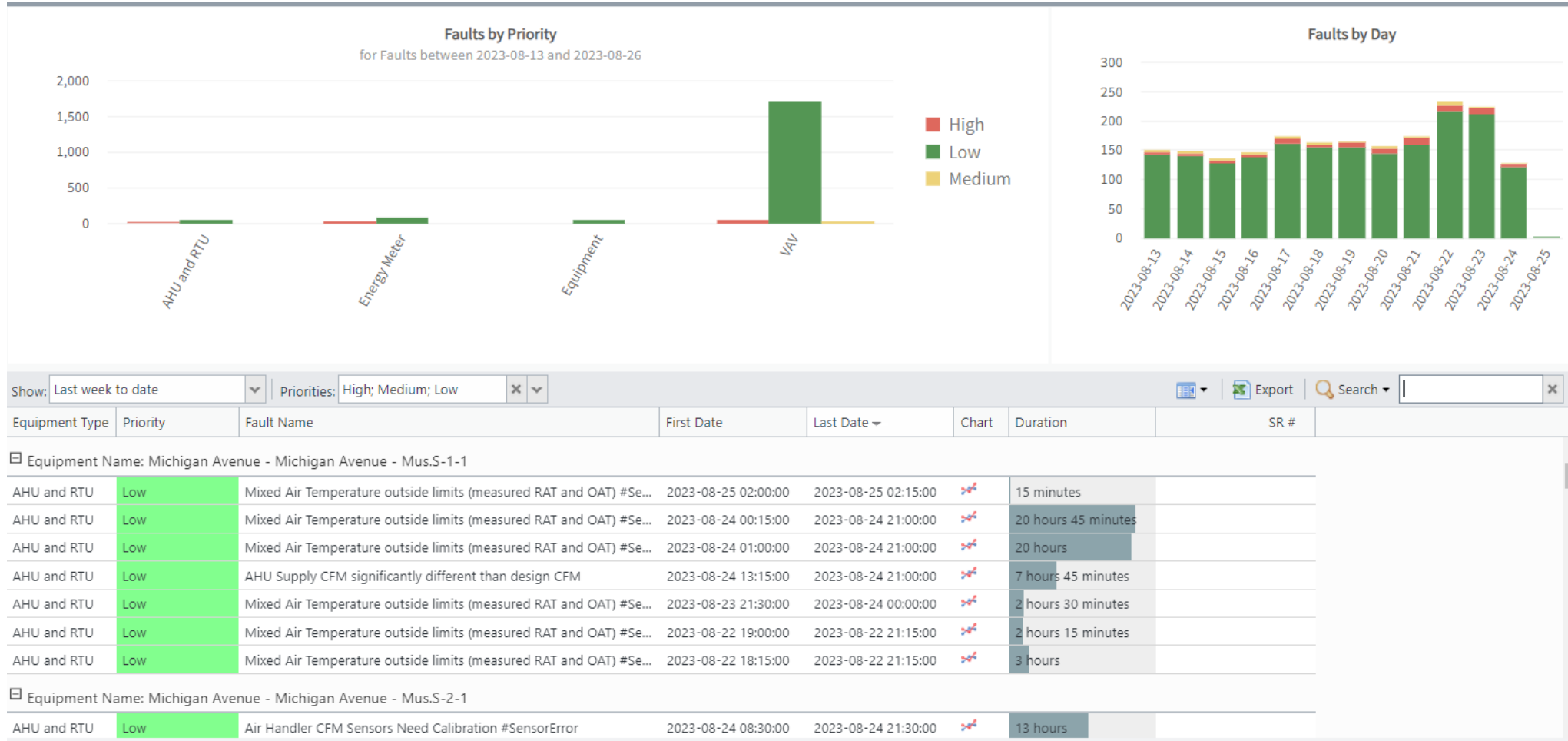


Building Automation System Monitoring

- 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



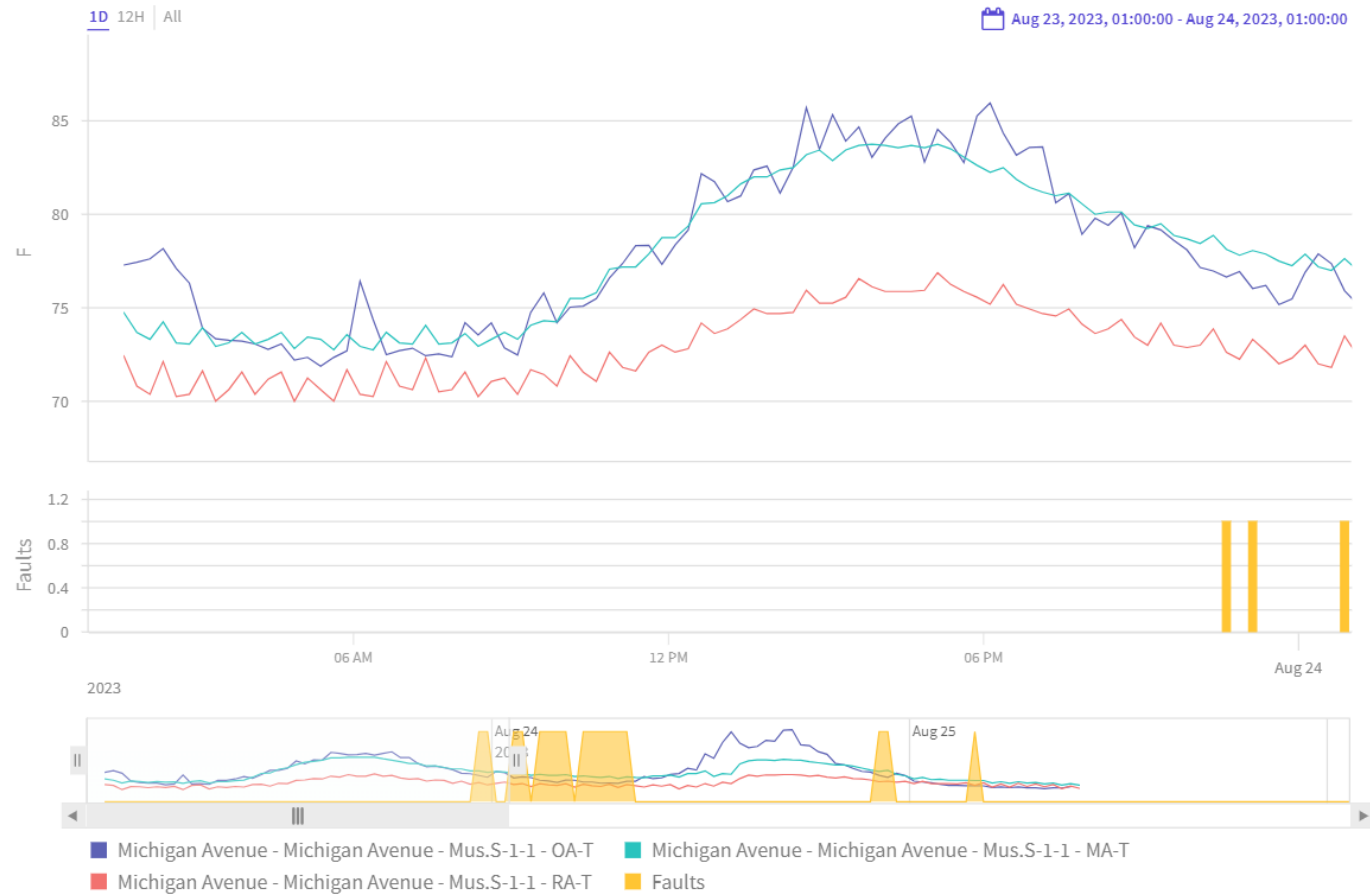
BAS Monitoring – Rules




BAS Monitoring – Rules

Points related to rule #59927. Mixed Air Temperature outside limits (measured RAT and OAT) #SensorError

Michigan Avenue - Michigan Avenue - Mus.S-1-1 - OA-T, Michigan Avenue - Michigan Avenue - Mus.S-1-1 - MA-T, Michigan Avenue - Michigan Avenue - Mus.S-1-1 - RA-T Readings between 2023-08-23 and 2023-08-26





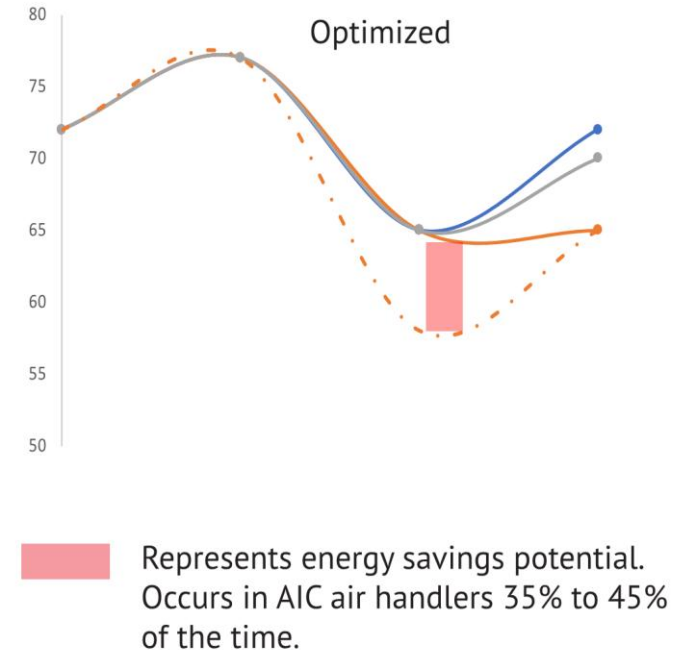
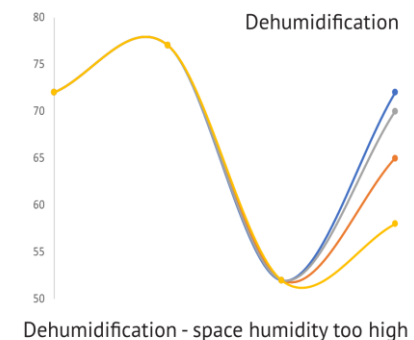
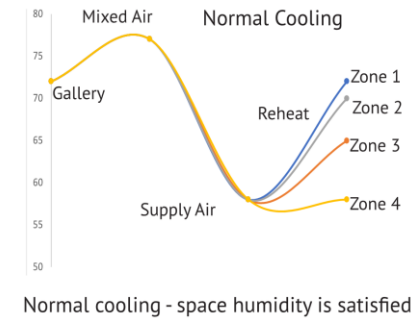
Machine Learning & Predictive Analysis



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



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?

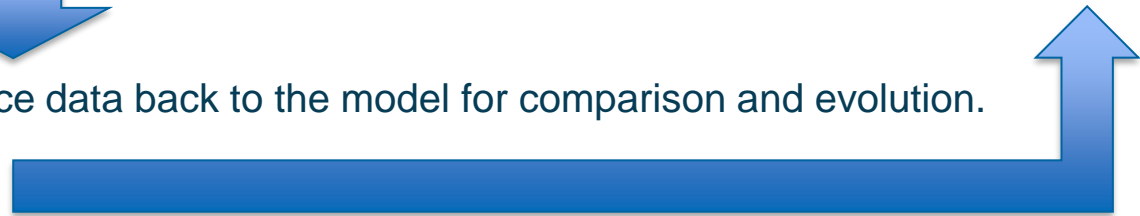
Build a Model: Using a third-party tool from Microsoft Azure toolset. This is the “Model” that sets DAT.



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

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

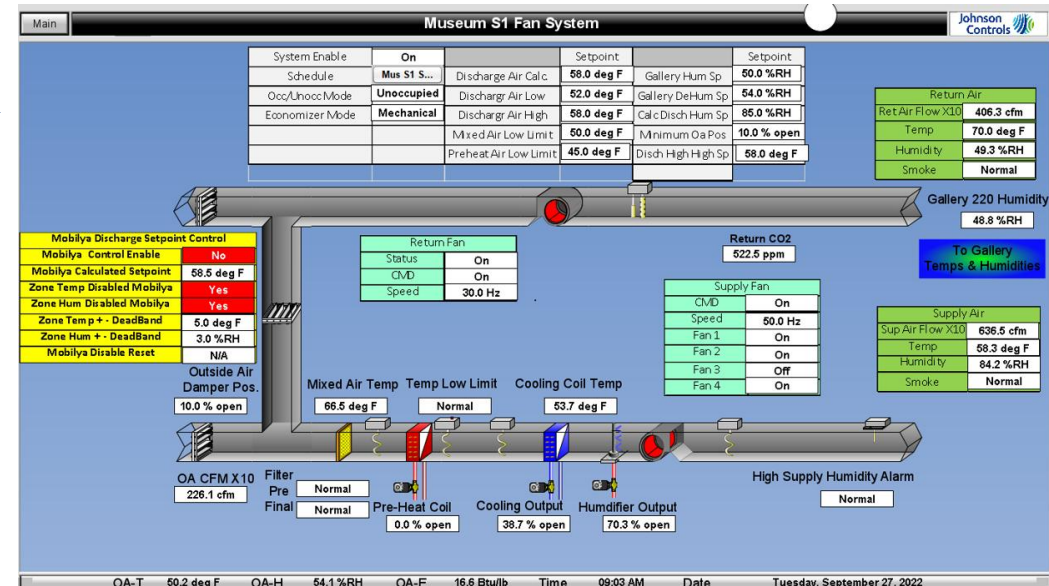
- Provide training data set, identify critical variables
- Develop machine learning model(s), select best characteristics
- Test with new data, known results
- Refine model
- Implement

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.

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.

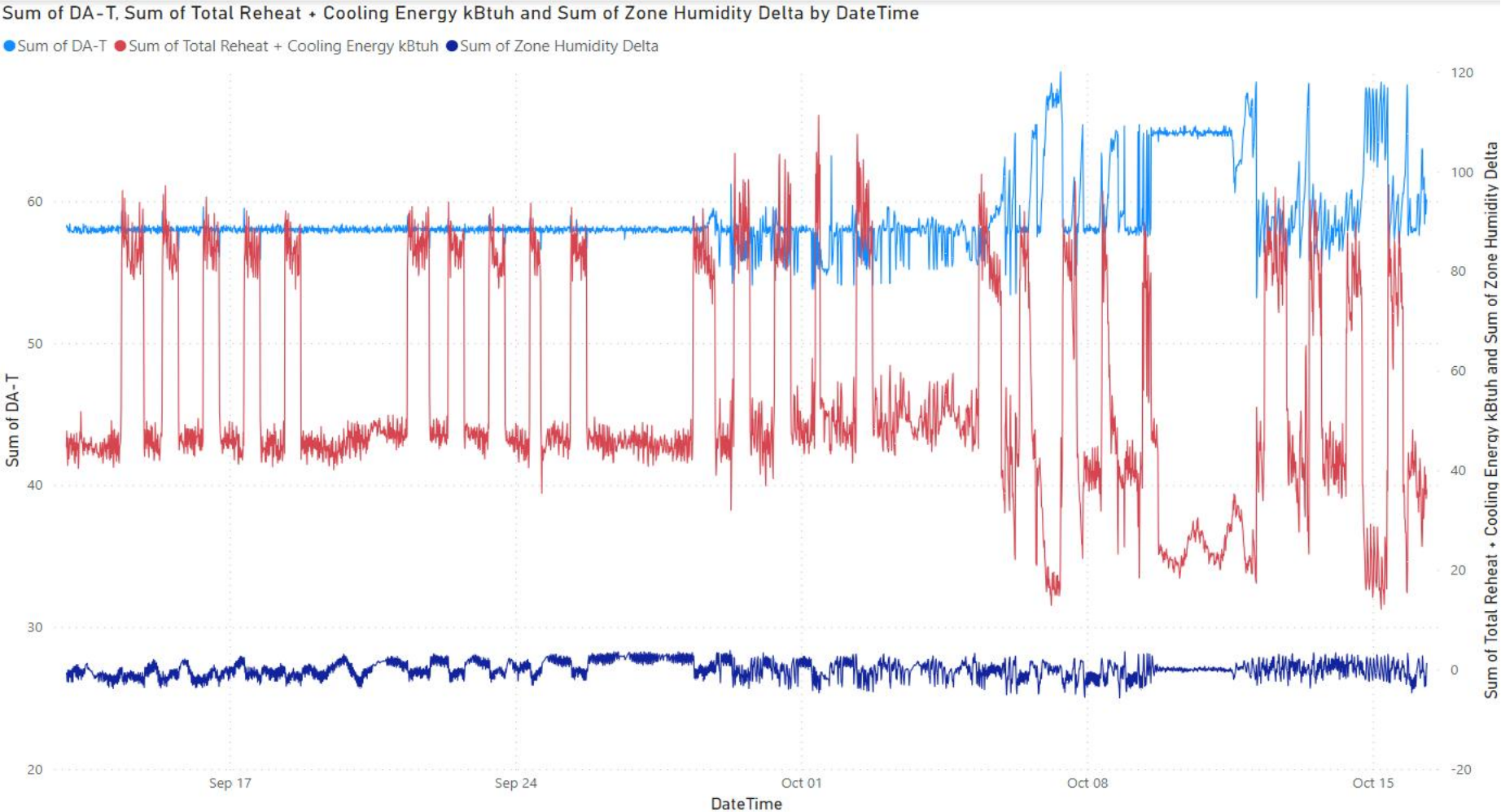
Results

- 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.

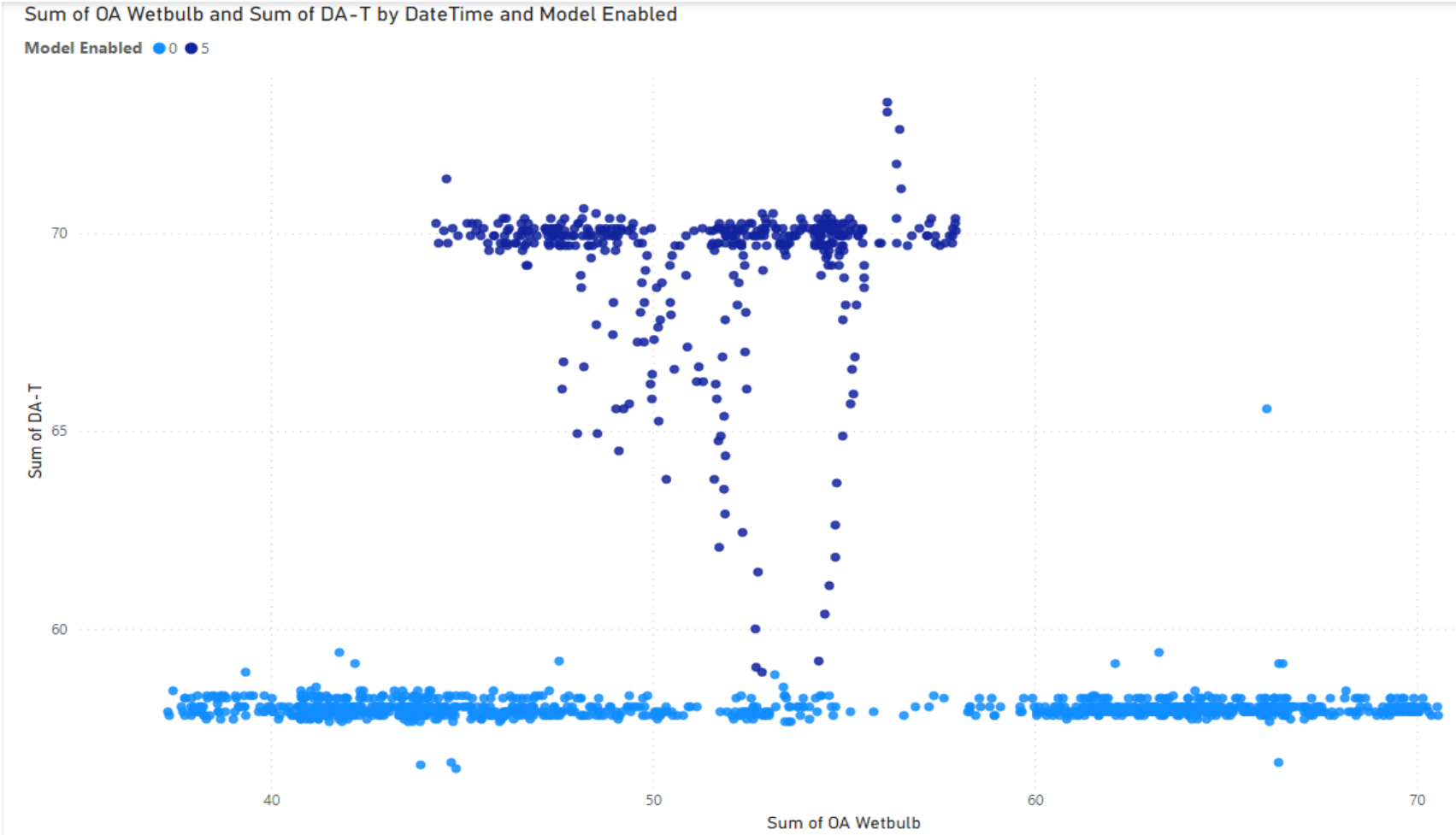
Results – Museum S1



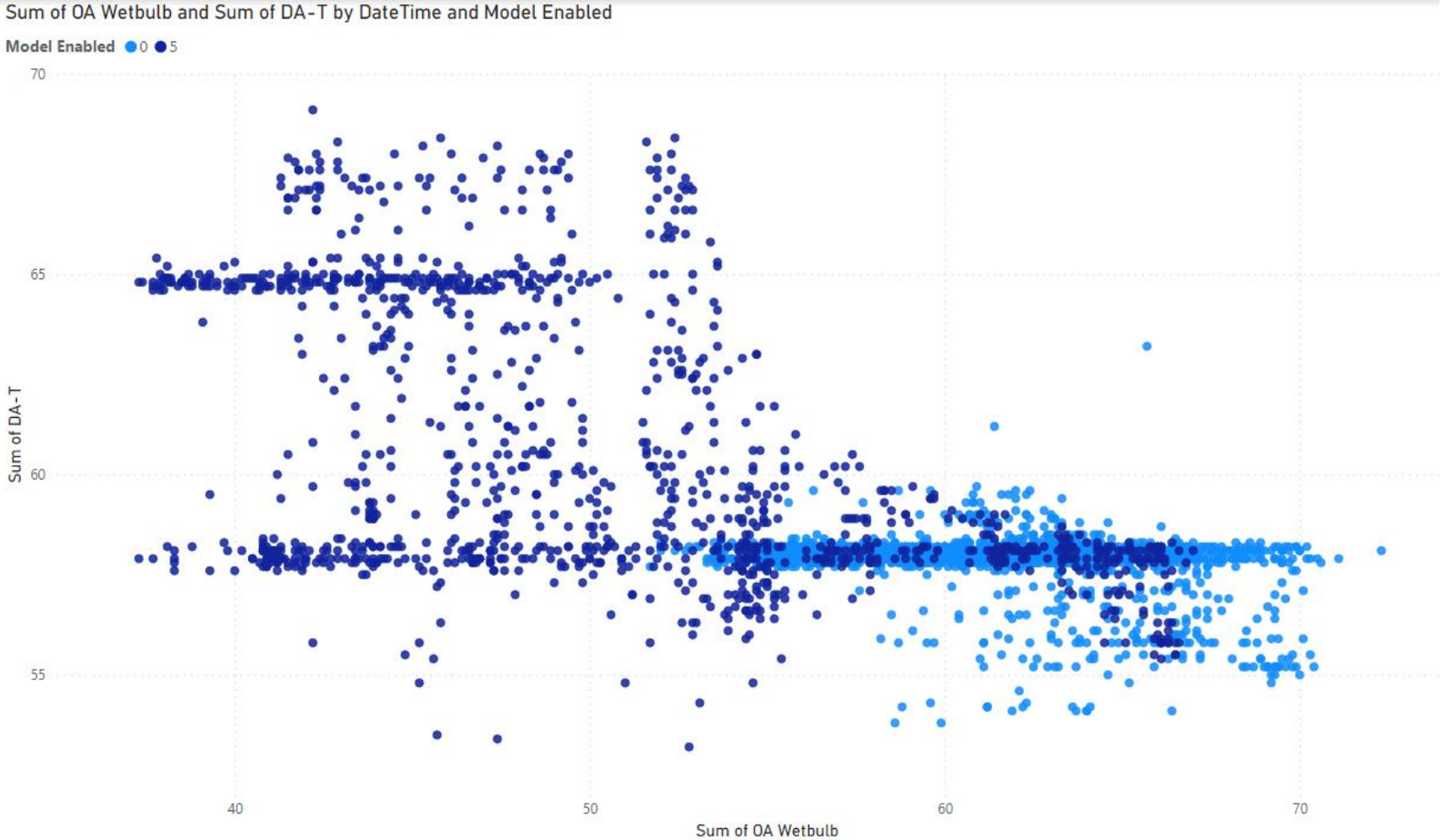
Results – Museum S2



Results – Museum S1 – OA Wetbulb vs DA-T



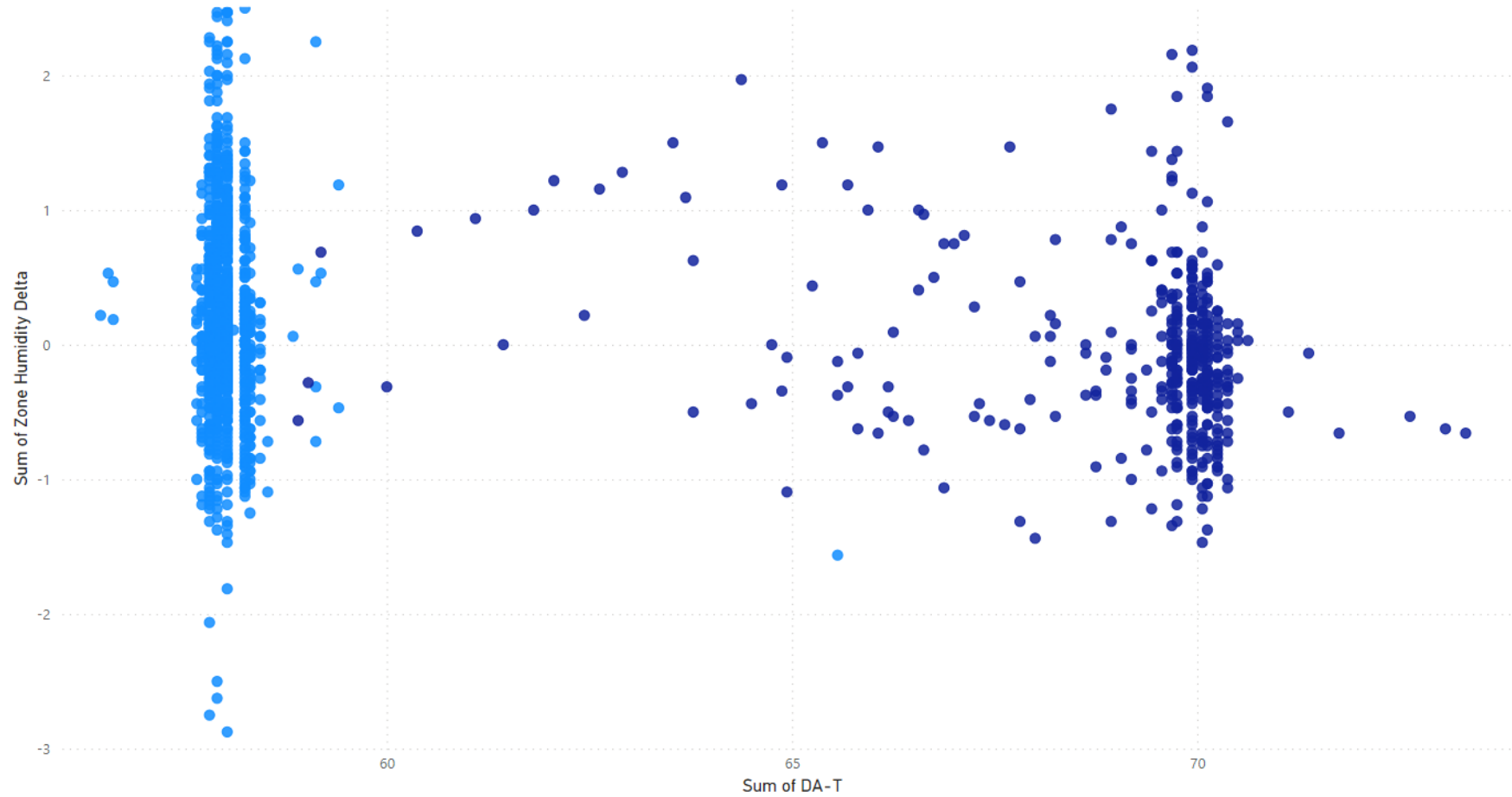
Results – Museum S2 – OA Wetbulb vs DA-T



Results – Museum S1 – DAT vs Humidity Delta

Sum of DA-T and Sum of Zone Humidity Delta by DateTime and Model Enabled

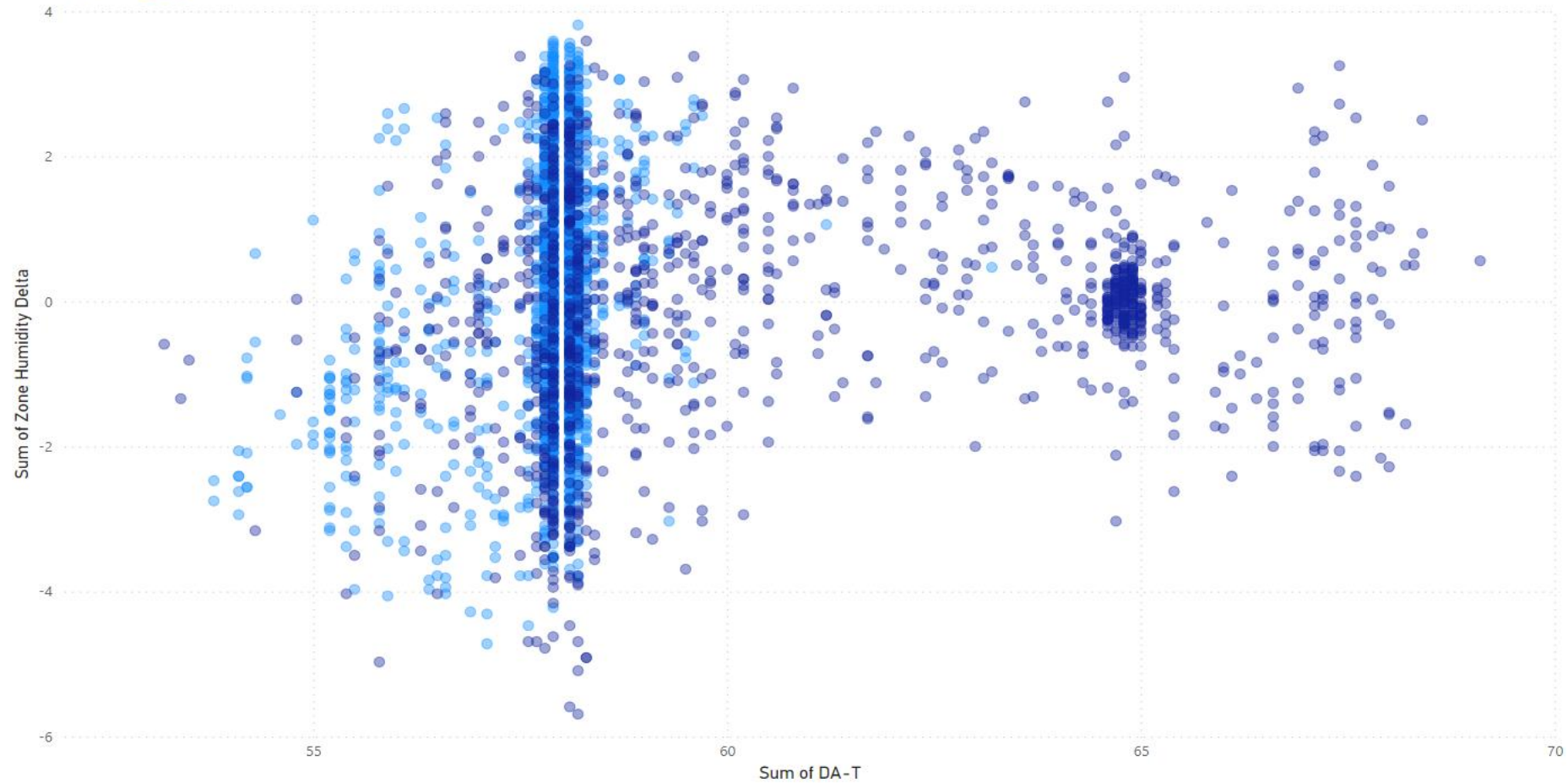
Model Enabled ● 0 ● 5



Results – Museum S2 – DAT vs Humidity Delta

Sum of DA-T and Sum of Zone Humidity Delta by DateTime and Model Enabled

Model Enabled ● 0 ● 5



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

Application Ideas

- **What opportunities exist to utilize ML/AI Today?**
 - **Heating & Cooling Plant Optimization (HHW/CW Setpoint, Variable Speed Pumping, Predictive Weather)**
 - **AHU Controls for Surgical & Patient Spaces (RH%, Static Pressure Reset)**
 - **Areas with dynamic loads.**
 - **Occupancy, ACH 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

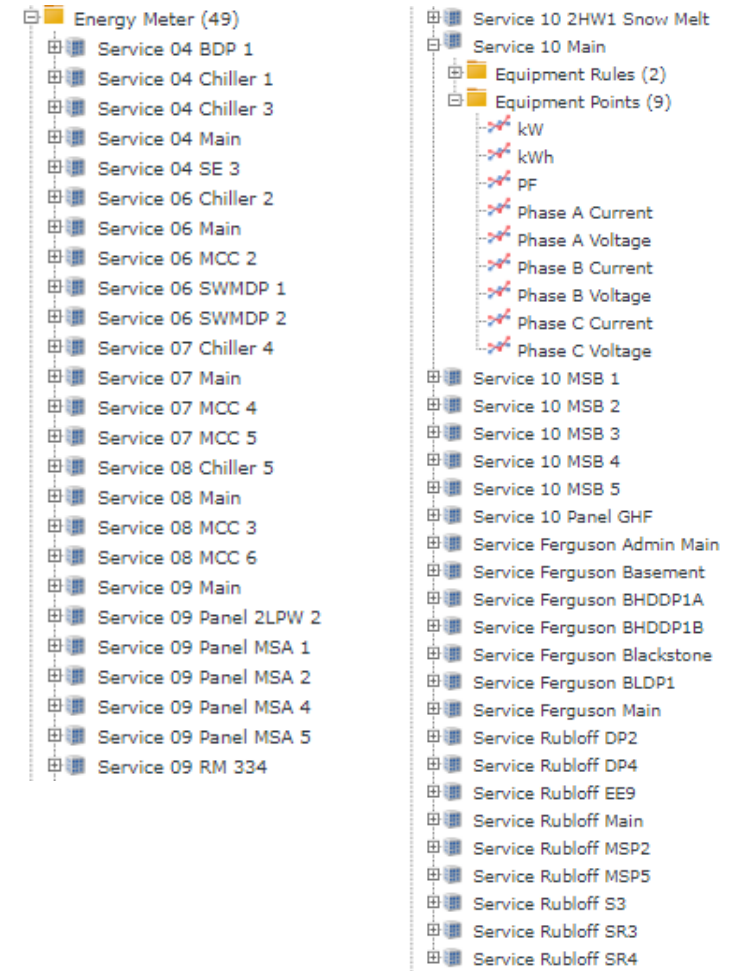
- Models are trained with historic data, but periodic retraining will be necessary
- Changes in the building will affect model prediction quality
- Provide critical parameters to operations team, impact of sensor replacement/calibration
- Be mindful of cloud computation costs when designing system, monitor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

Panel Level Monitoring

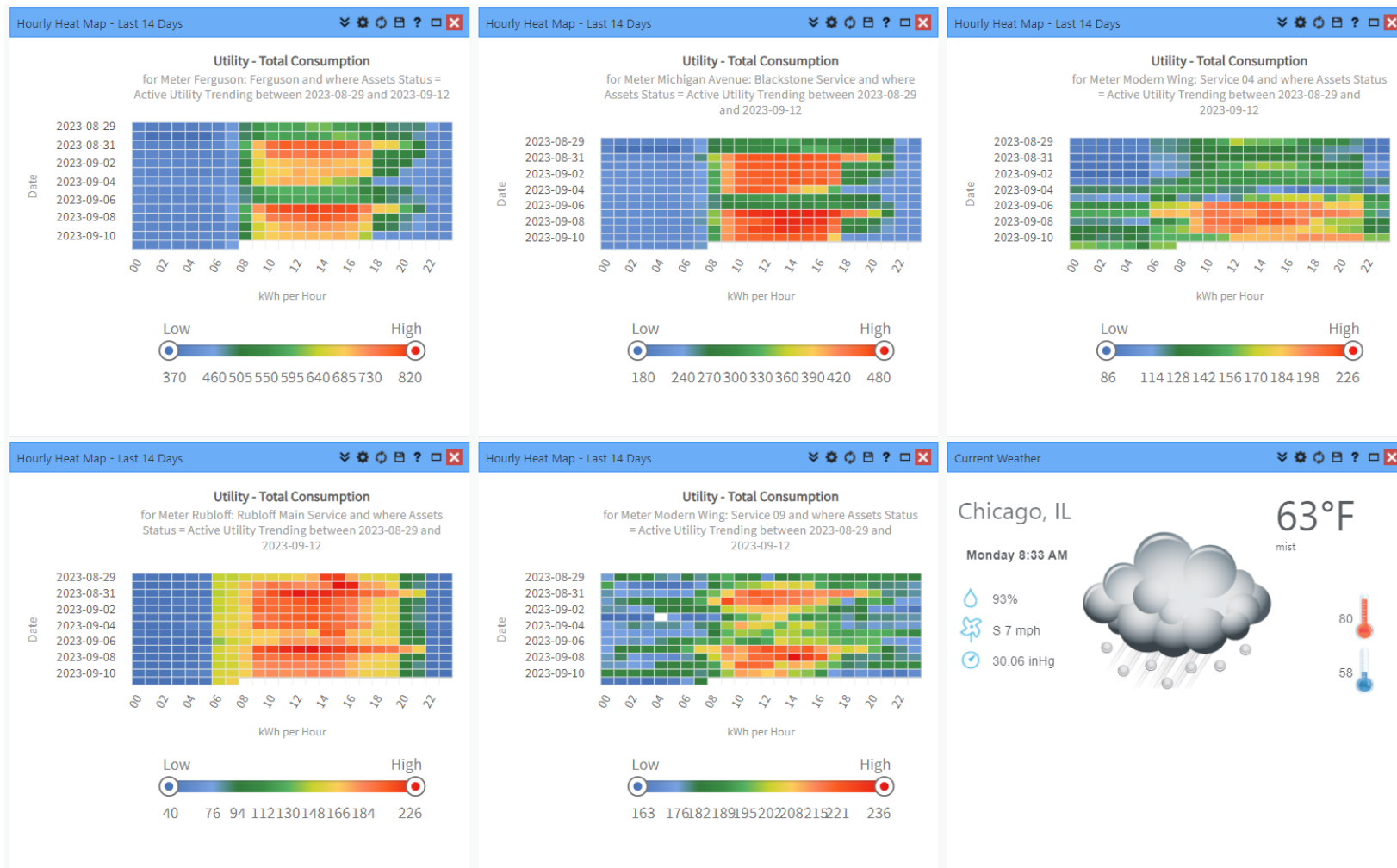
- Collecting kW, kWh, Volts, Amps, Power Factor
- Data collected for a period to identify baseline
- Create rules to identify anomalies on major equipment, panels
- Flexible rules, day/night, weather dependent

Rule Details		Rule Faults						
Equipment Type	Priority	Fault Name	First Date	Last Date	Chart	Duration	SR #	
Equipment Name: Modern Wing - Service 07 Main								
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						
Equipment Type	Priority	Fault Name	First Date	Last Date	Chart	Duration	SR #	
Equipment Name: Modern Wing - Service 04 Main								
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	

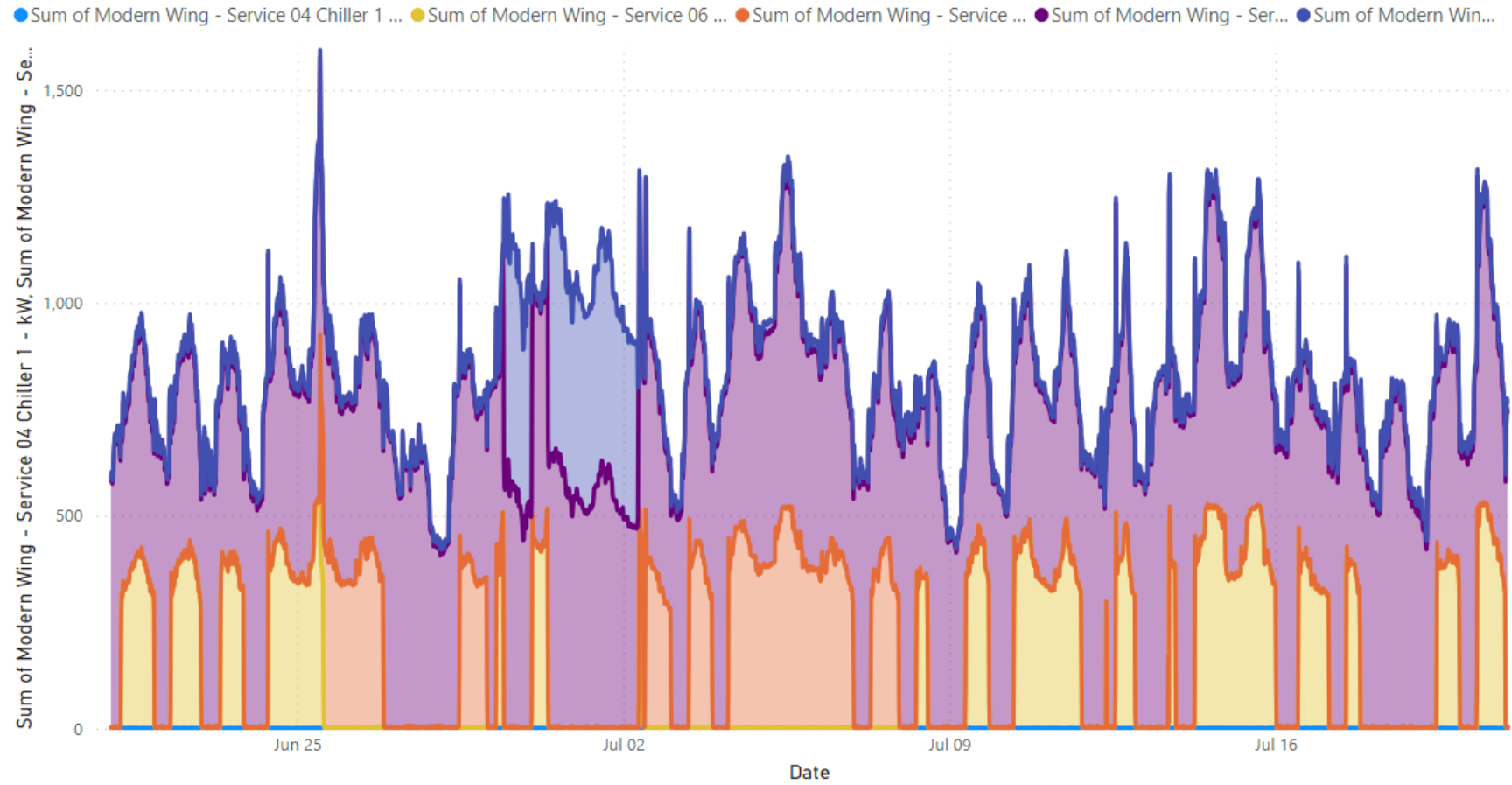


Panel Level Monitoring Dashboard



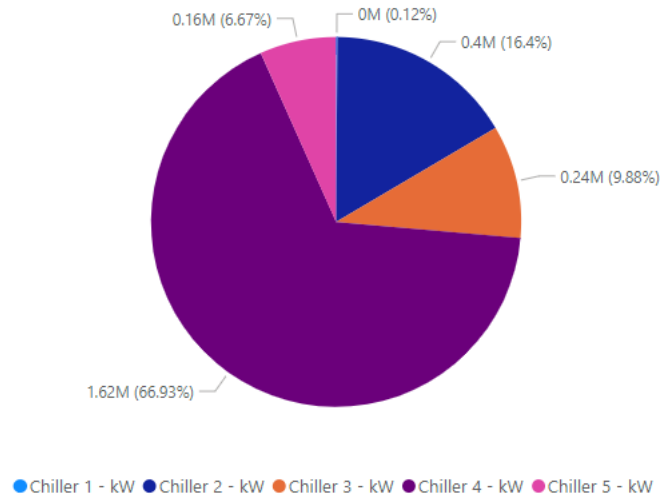
Campus Metering - Chillers

Utility Meters - Chillers



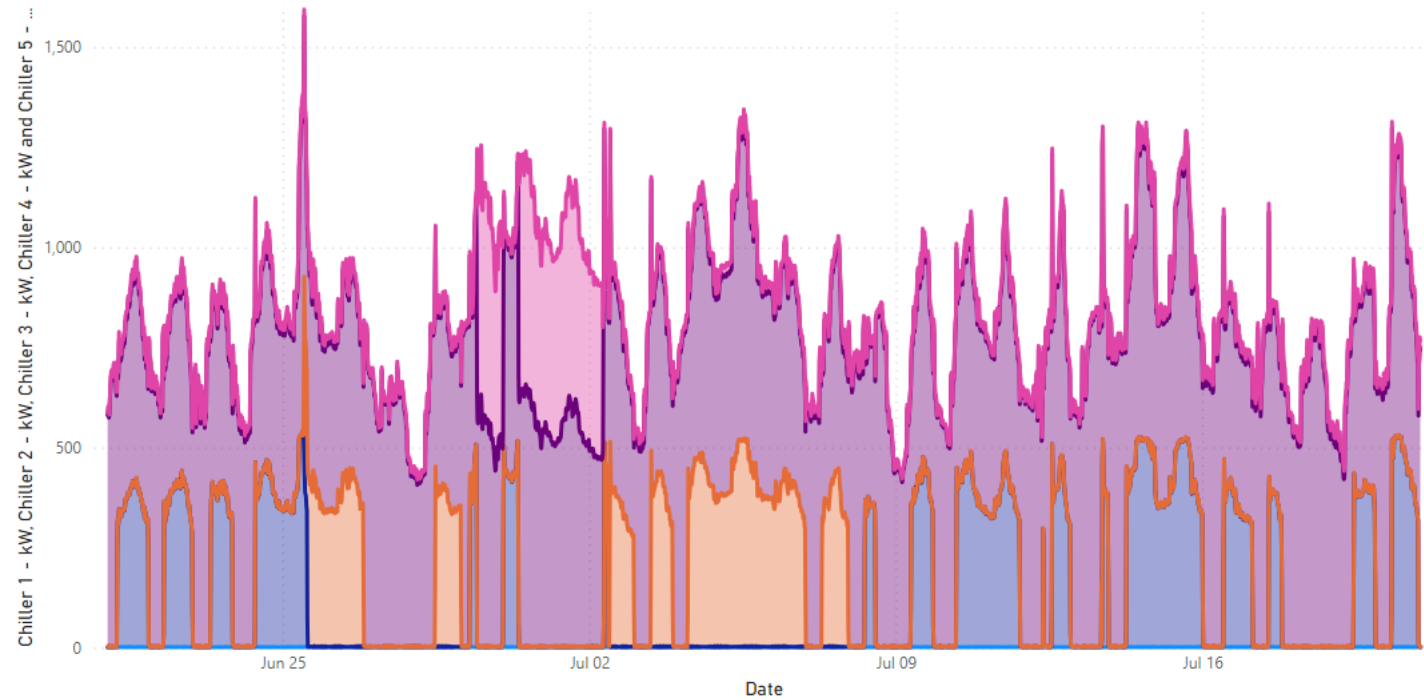
Chiller Plant Energy Consumption

Chilled Water Energy Consumption



Submeters - Chillers

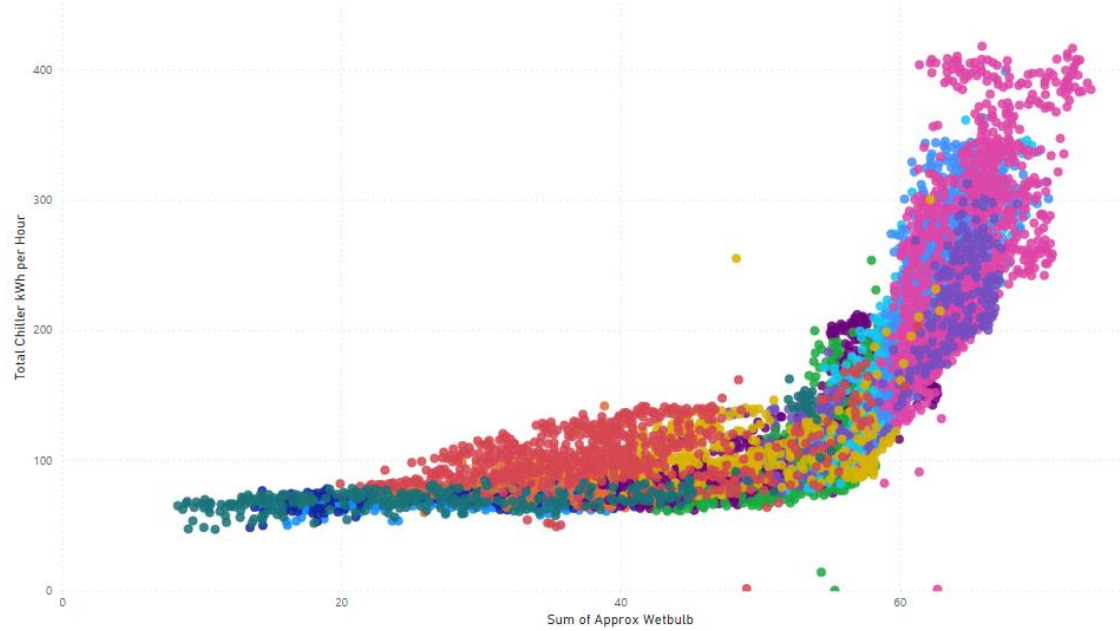
● Chiller 1 - kW ● Chiller 2 - kW ● Chiller 3 - kW ● Chiller 4 - kW ● Chiller 5 - kW



Chiller Plant Energy Consumption

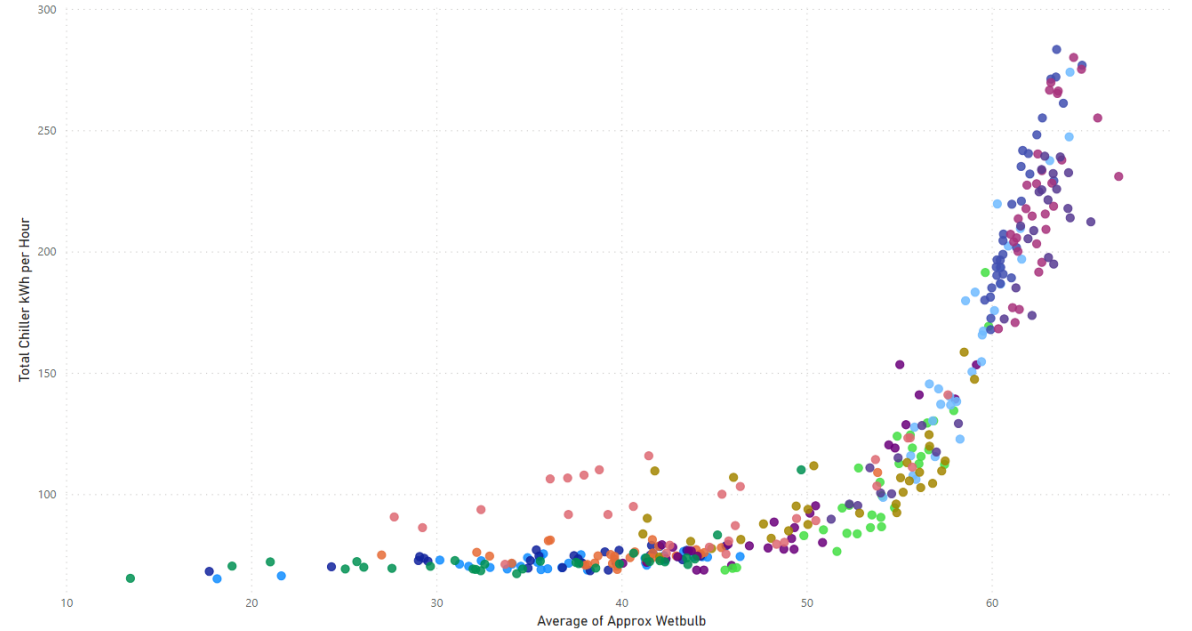
Chilled Water Plant Consumption by Wetbulb Temperature

Month January February March April May June July August September October November December



Chilled Water Plant Consumption by Wetbulb Temperature

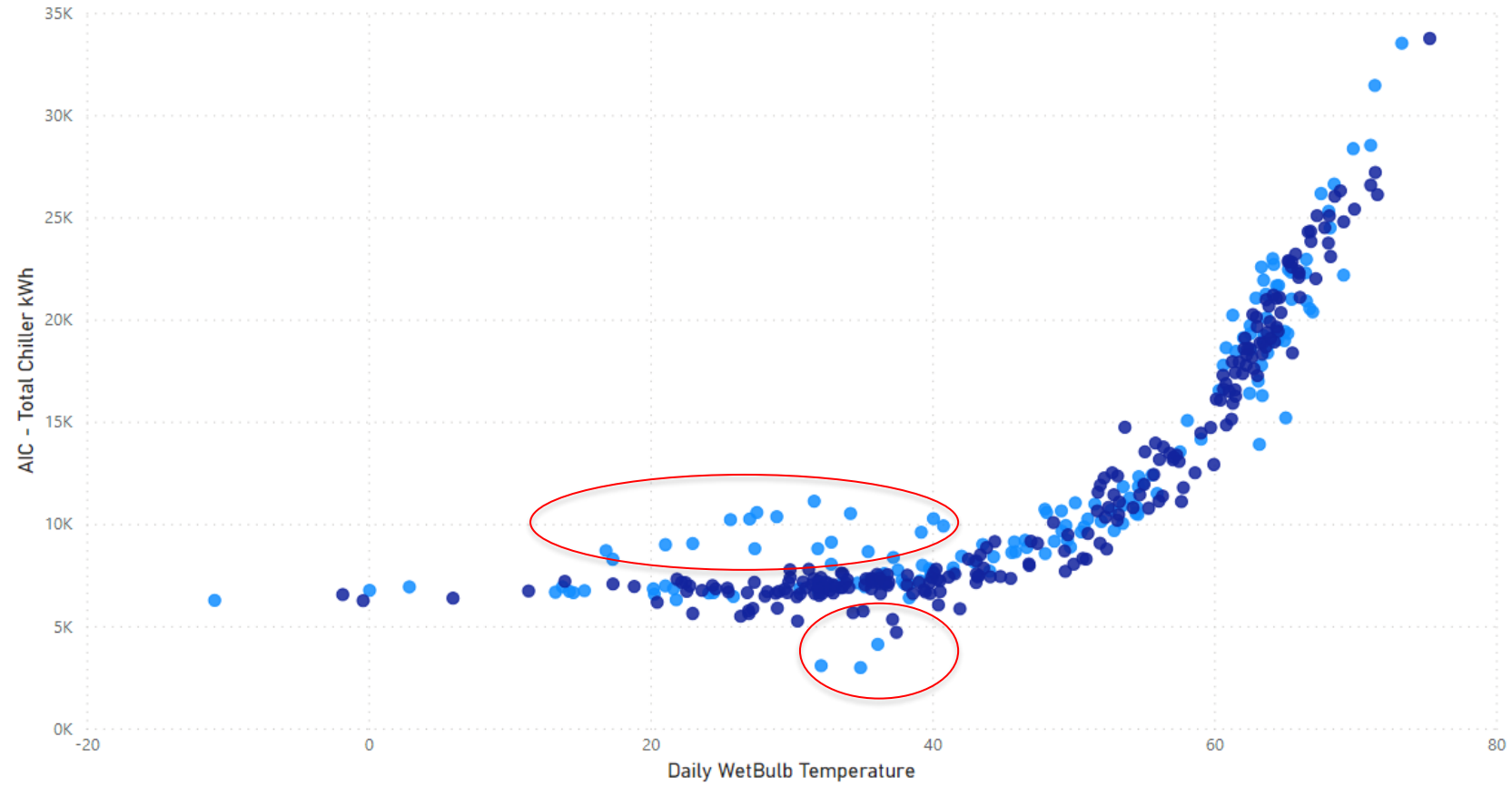
Month January February March April May June July August September October November December



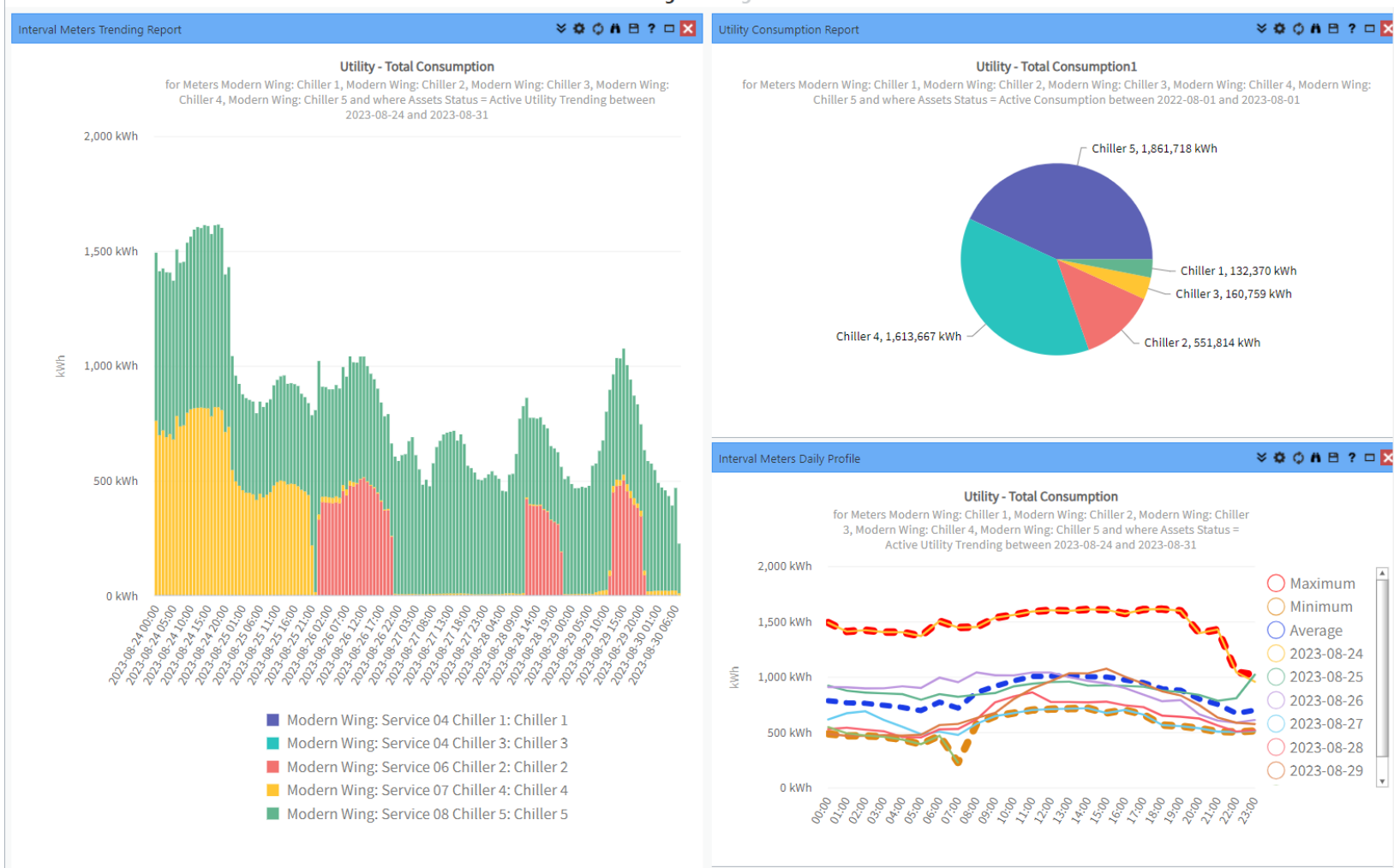
Chiller Plant Energy Consumption

Sum of Approx WB and Sum of Total Chiller kWh by Date and Year

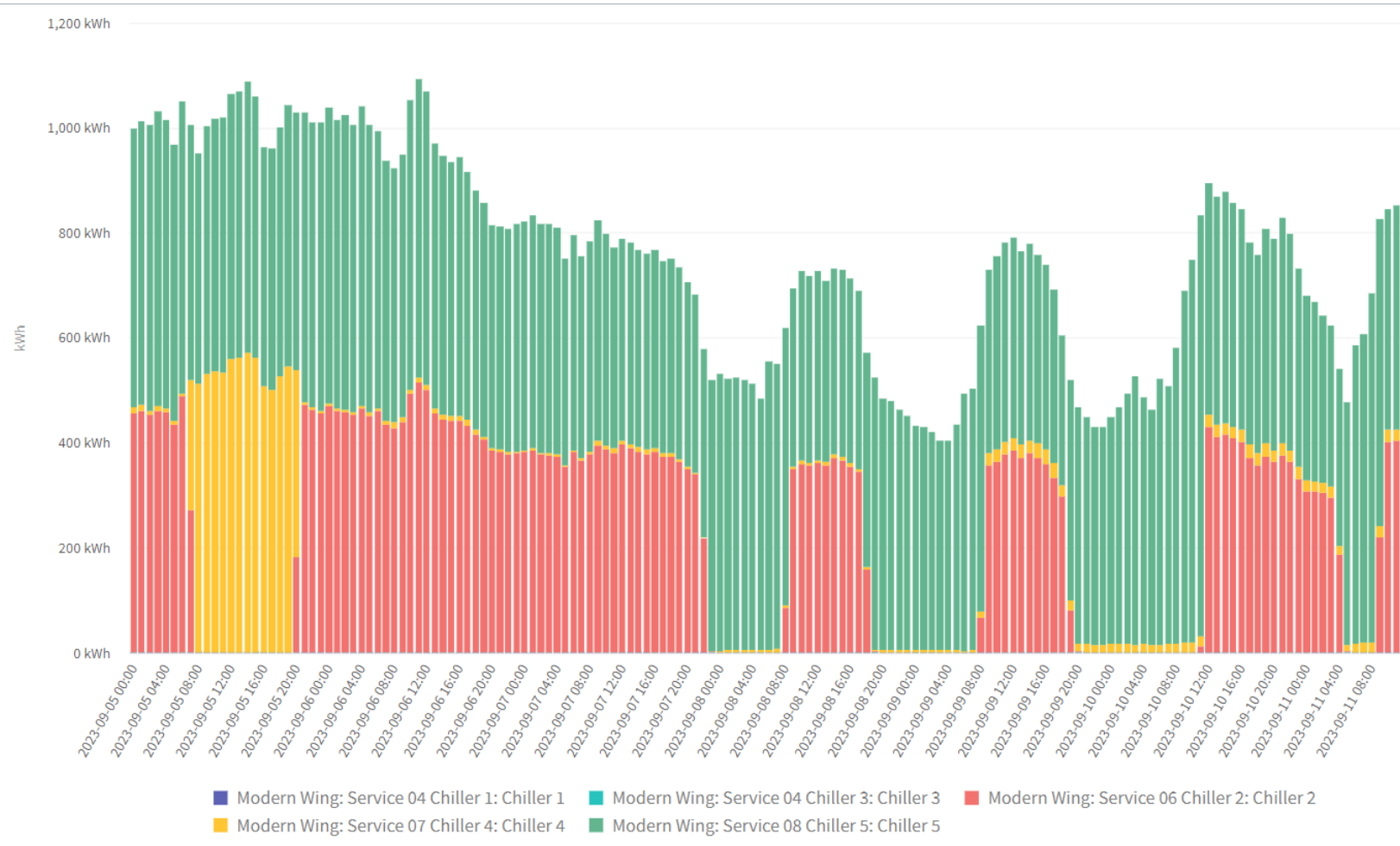
Year ● 2022 ● 2023



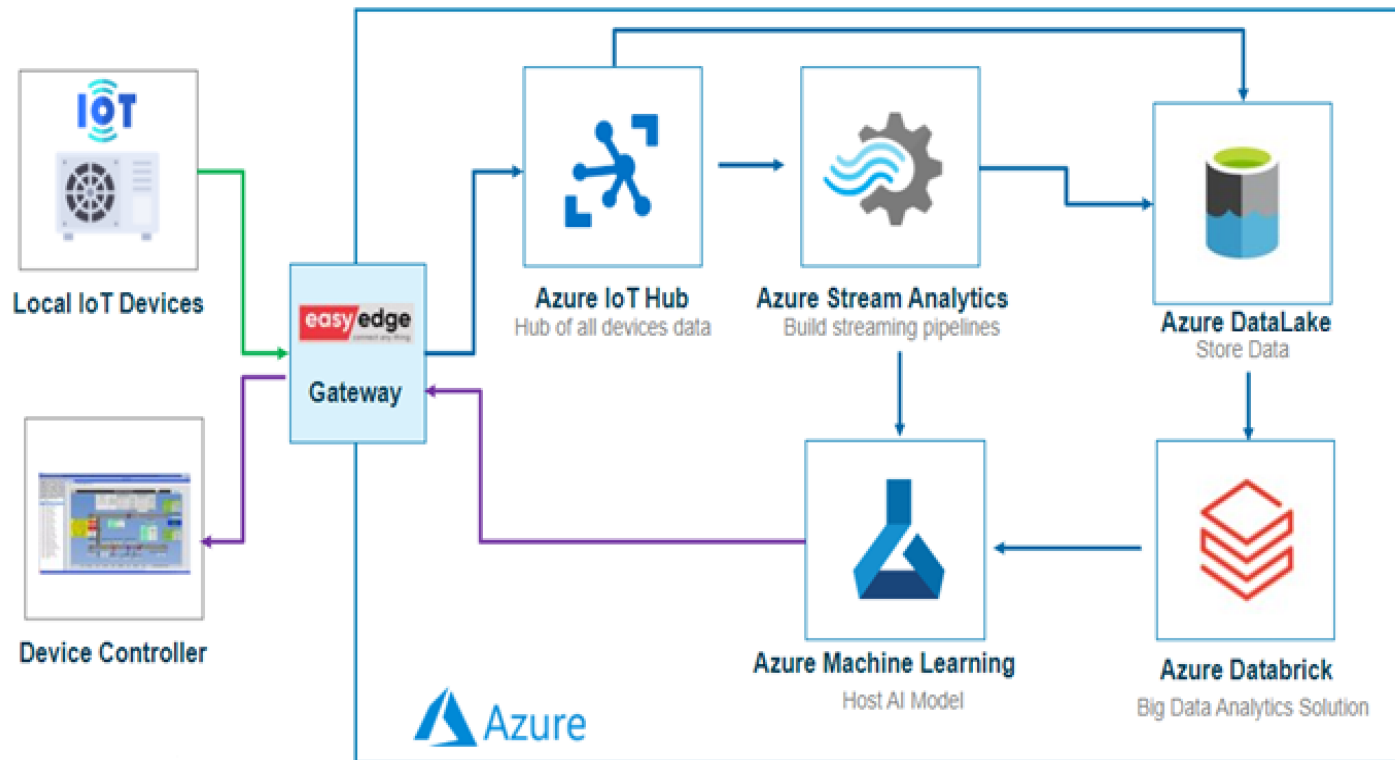
Chiller Energy Dashboard



Chiller Energy Tracking



Machine Learning – Data Flow



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