



Informatics Driven Central Plant Optimization

Presented by: Alex Huang, Kayvan Torkashvan, Don Guan

Division of Technical Resources National Institutes of Health

NIH and What We Do

A federal government agency
Annual research funding ~ \$37 billion
27 biomedical research institutes
75 buildings over 300 acres
Total building area~12 million sqft
Houses world-class 240-bed research hospital











NIH Central Utility Plant (CUP) Overview

One of the largest CUPs under one roof in the USA

Provides campus with chilled water, steam, electricity, and compressed air

CUP Components

Twelve 5,000 Ton capacity chillers
7.75 million gal CHW thermal storage tank
5 million gal Industrial Water System
Five gas/ diesel dual fuel fired boilers
800 KPPH, 980 KPPH with Cogen
Cogeneration Power Plant

One of the largest US government Cogen plants
One of the cleanest Cogen plants in the world
23 MW, 180KPPH steam (40% of campus demand)







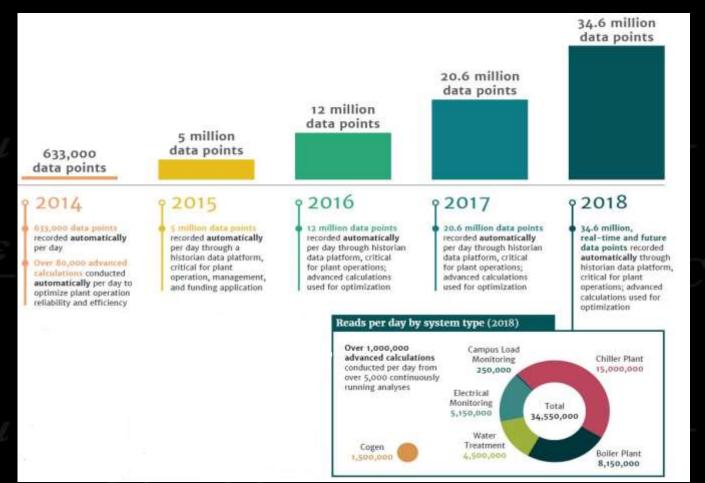
TES and chiller controls upgrade project presentation will be 3:00 PM today

TES tank

IWS tank

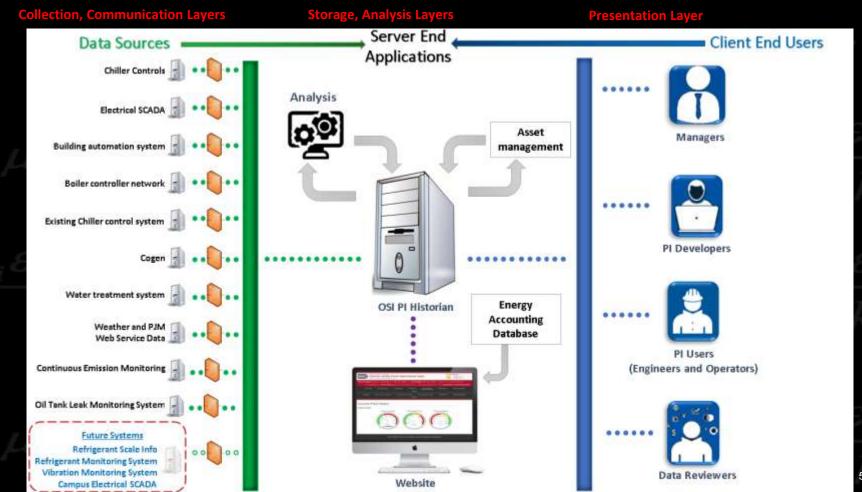
DIVISION OF JECHNICAL KE

Data Platform - Heart of Actionable Operational Intelligence



4

Enterprise-level Cross Platform Data Integration



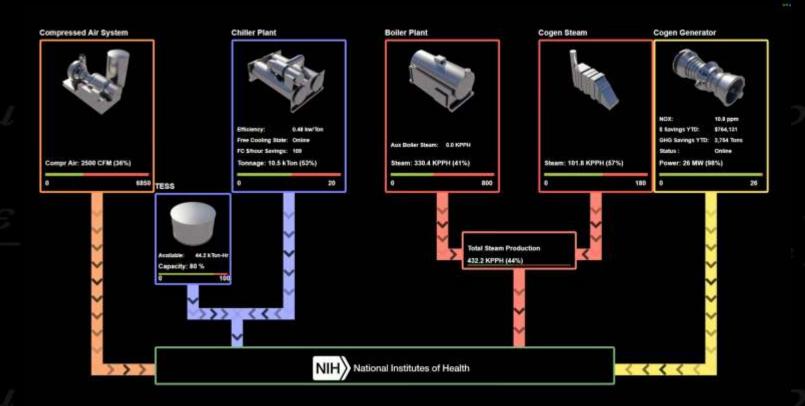
Web-based Executive Level Summaries and Reporting

Executive daily performance and operation data accessible with 1 click:



(Not the actual data

Dynamic CUP Dashboard



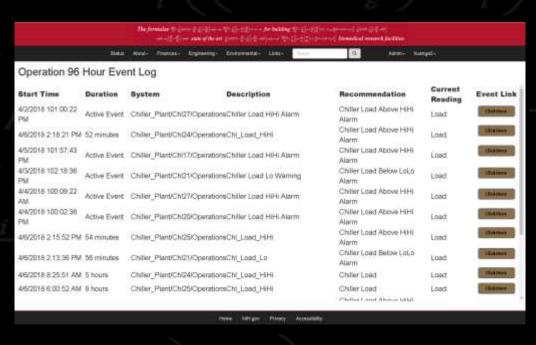
Data Platform Powering the CUP Control Room

The real-time, actionable data drives operations from reactive to proactive.



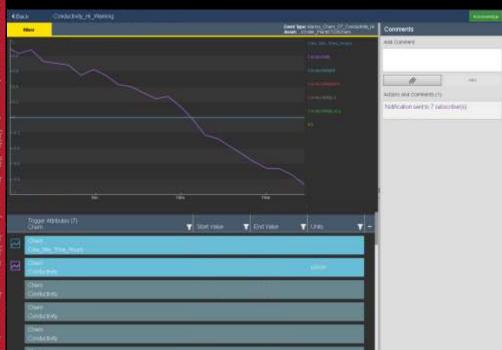
Actionable Operational Intelligence & Fault Detection

Data Platform provides operators actionable intelligence, in-time RCA, and helps review operators' performance





Alarm Notification and Mobility





Digitization Plant Operations - Round Data Entry Website

		Water Ch	nemistry Data Entry	<i>'</i>
Boller RO	MB TESS/WS			
Select Date				
Select Hour *	()			
1000				
c:				
City Wat	er			
Conductivity		(µ5/cm)		200 - 600
~	Prince Connector	Databaset\Chemical_Treatment\Boller_Plant\City\Ope	ar stor. PromptalConductivity	
	User	Submitted at	Value	Value timestamp
	NIHYohnba	1/17/2019 10:55:19 AM	123	1/17/2019 10:55:19 AM
	NIH'ýohnba	1/18/2019 10:25:19 AM	234	1/18/2019 10:25:19 AM
	NIHYohnba	1/19/2019 10:59:40 AM	345	1/19/2019 10:59:40 AM
	NIHVohnba	1/20/2019 11:08:41 AM	456	1/20/2019 11:08:41 AM
	NIH\johnba	1/21/2019 11:05:29 AM	567	1/21/2019 11:05:29 AM
	NIH\gomesaj	1/22/2019 12:00:41 PM	678	1/22/2019 12:00:41 PM
	NIH\gomewj	1/23/2019 10:31:42 AM	789	1/23/2019 10:31:42 AM
Hardness		(ppm)		
>			-4	
Total Alkalinity		(ppm)		9
Reset Entry	Fields			
Submit				(Not the actual data)

Risk Management - Weekly Boiler Plant Chemical Dashboard

Boiler Round Data

Boiler Fee	d Wat	er Rou	nd	
Description	Value	Units	% compliar	ice.
Conductivity Daily Rounds		uS/cm		
plt Daily Rounds			100	
27 Concentration Sully Rounds		pph	100	Ī
Hardness Daily Rounds		ppm	90	
Description	Value	U.III	% complia	nce
Steam Condens	Listanoi			
CRC Arriage Daily Round		- ppm	A Compile	
Enc resile bary roung	-	SALAH.		
Soft W	ater R	ound		
Description	Value	Units	% complia	nce
Hardness Daily Rounds	1000	ppm	100	
ŧ	B Rou	nd		
Description	Value	Units *	compliance	4
Feed ORP Round Data	200000	mV		
had Water Conductivity from Date		uS/cu		1
		_		

RO 1 Round				
Description	Value	Units	% compliano	ie
Inlet Hardness Daily Roun	in the state of		90	Ī
Inlet ORP Daily Rounds		πИ	98	
RO filter pressure drop				
Outlet Conductivity Daily	in care of	uS/cm	95	Ī
Outlet pH Daily Rounds	interior.		100	
Inlet pH Daily Rounds	0110110		90	

RC	2 Ro	und		
Description	Value	Units	% compliar	voe:
Inlet Hardness Daily Round			100	
Outlet ORP Daily Rounds		mV		
RO filter pressure drop				
Outlet Conduction by Opiny Rounds		uS/c	96	
Outlet pH Daily Rounds			100	
Inlet pH Daily Rounds	-		92	

Boiler 1-5 Conductivity Live			
Description	uS/cm	% compliance	
Boiler 1 Consulctivity		100	
Boiler 2 Conductivity		100	
Boiler 3 Conductivity		100	
Bailer & Conductivity		100	
Bailer 5 Conductivity		100	

Boiler 1 Rounds			
Description	Ppm	% compliance	
Palk Daily Rounds		98	
Polymer Daily Rounds		97	
Suffice Daily Rounds		91	

Boller 2 Rounds			
Description	PPM	% сопрівлее	
Palk DAily Rounds		88	
Polymer Daily Rounds		97	
Sulfite Daily Rounds	C MANU	95	

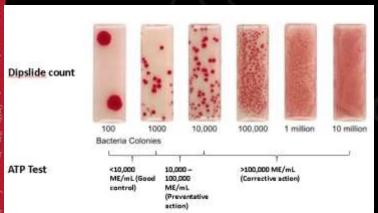
Boiler 3 Rounds				
Description	Ppm	% compliance		
Palk DAlly Rounds	nuro er	90		
Polymer Daily Rounds	5800	100		
Sulfite Daily Rounds		68		

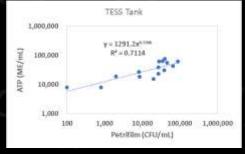
Boiler 4 Rounds				
Description	Ppm	% compliance		
Palk DAlly Rounds	350	100		
Polymer Daily Rounds	418	100		
Sulfite Daily Rounds	180	97		

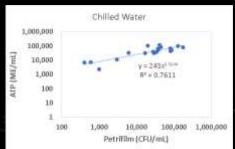
Boiler 5 Rounds				
Description	Ppm	% compliance		
Palk DAily Rounds	nivel.	89		
Polymer Daily Rounds		95		
Sulfite Daily Rounds		97		

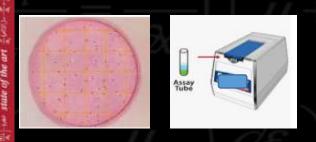
Ongoing Project - Rapid ATP-2G Detection Technology

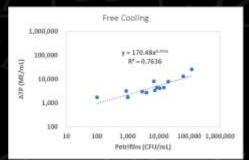
ATP, DipSlides, Petrifilm correlations

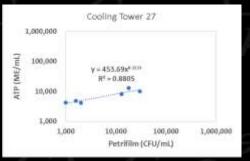












Digitization Plant Operations - Operator Shift Turn Over Website

Asset status, work orders closed and submitted, alarms, misc. events, live log, message to the next shift



Digitization Plant Operations – Steam Turbine Readiness Checklist website

Steam Turbine Start up Preliminary Checklist

Chiller 22/23

Operator



Ensure that the three condenser and surface condenser isolation valves are properly lined up

The surface condenser water inlet valve (SCIV-22) and the surface condenser outlet valve (SCOV-22) should be **Open**, and the condenser outlet valve (COV-22) from the chiller condenser should be Closed.

Operator



Ensure that the chiller and condenser barrels have been properly vented.

Operator



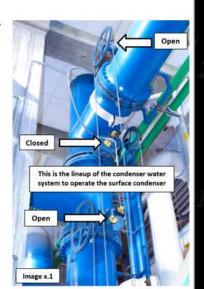
Ensure that the emergency stop button is pulled out.

CT roof level

Chiller 22/23

MCC

urface condenser

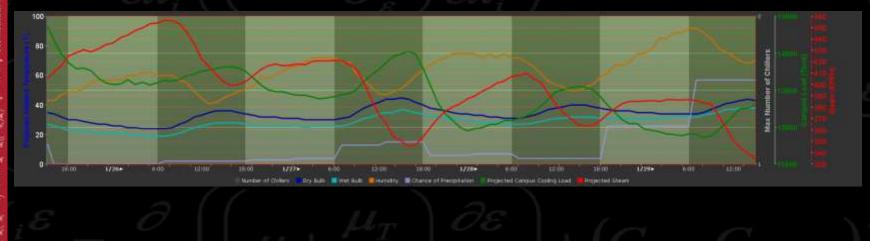


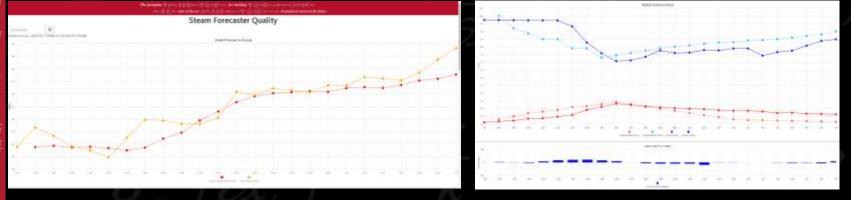
Machine Leaning / Statistical Modeling Methods

Supervised Learning Unsupervised Learning

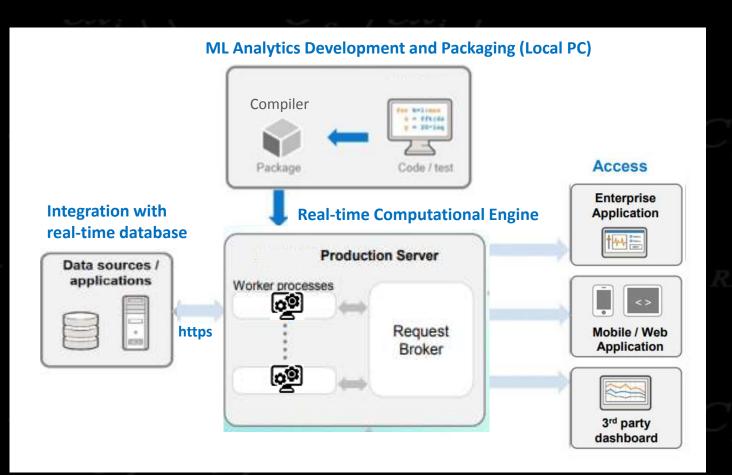
Discrete	Classification or Categorization	Clustering
Continuous	Regression	Dimensionality Reduction

ANN based Load Forecaster and Online Error Analysis

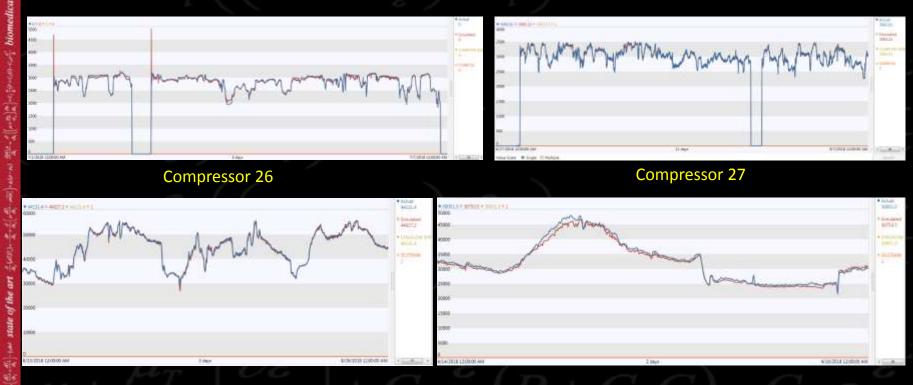




Streaming Machine Learning Calculations Architect



Real-Time Machine Learning Integration: Simulated Compressor Performance



Steam-driven Compressor 23

Steam-driven Compressor 22

Ongoing Project – Operator Simulator Project

Operator training on normal and emergency scenarios, situation playback, evaluate innovative control strategy and optimize the process



Chiller Plant Optimization

Objective function: Minimize (the total equivalent cost in next 48 hrs)

The individual component models are from machine learning models

The Constraints:

- · Chiller run time and availability
- Electrical feeder load balance
- Limits of the individual chiller /free cooling capacity, flow, temp, etc.
- TES tank status and capacity
- Load Forecasting and Energy Balance
- Future PJM Electricity Price

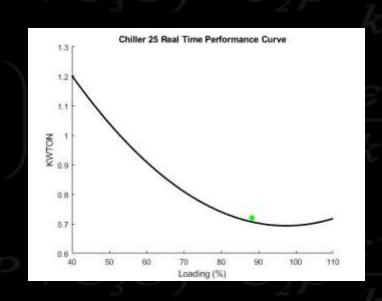
The Decision Variables:

- The chiller condenser evaporator flow, temp
- The load distribution among the chillers
- Free cooling flow, number of heat exchangers
- TES charge / discharge dispatch decision and flow

Asset Availability Website



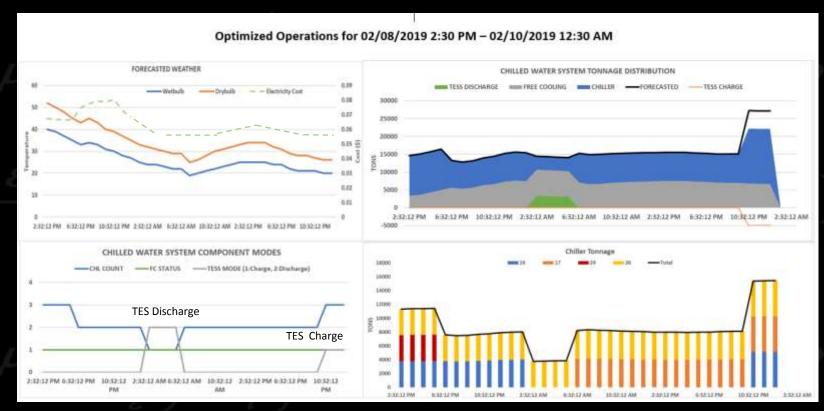
Optimization Animation



Optimization Results and Recommendations

Typical Suggestions:

Run minimum number of chillers, shift more load to free cooling, the more efficient chillers or the steam turbine chiller, run more cooling tower cells to reduce the tower return temp, or increase the chilled water supply temp.



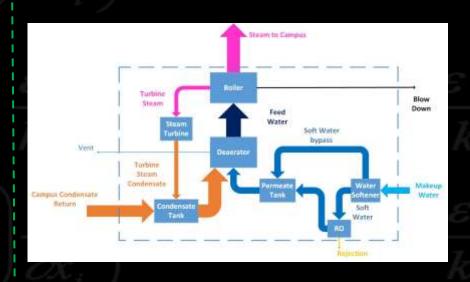
Data Quality Life Cycle Management

Data Generation



Calibrate and maintain the sensors
Fix the data / interface communication errors
Online statistic scan
Identify the incorrect and missing data
Clean and smooth the data
Error propagation and metrological standards

Data Utilization



Calculation Handbook and Change Management SOP
Daily / Monthly Dashboard Review SOP
Machine baseline and health check
Energy / mass/ cost balance and cross disciplinary check
Auto Fault Detection, text message & emails notifications

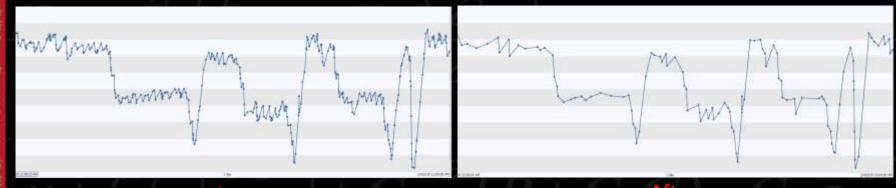
SQC Signal-Noise Based Data Compression and Clean Process

Goal:

- Obtain reliable post-processed data
- · Actionable plans based on more reliable and trusted data without too much need for post processing.

Results:

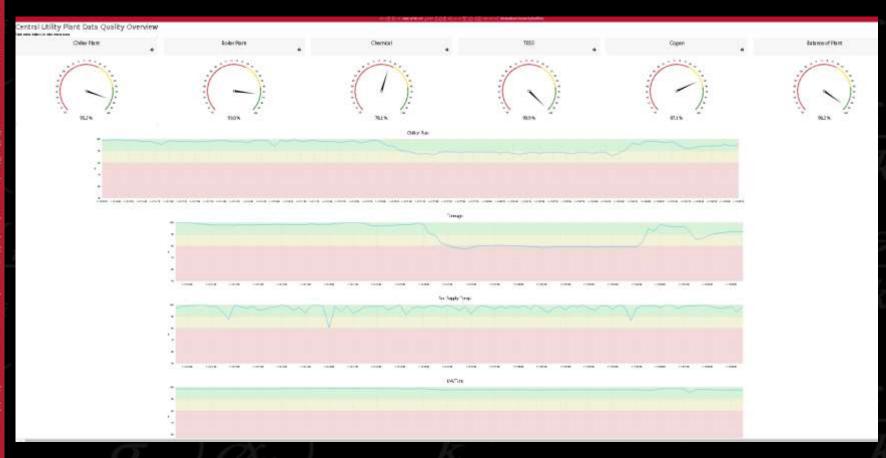
- Saved hours of time spent on post processing the noise.
- Less space used on server
- Less load on server
- Cost savings for plant operation due to better data for forecasting and optimization modeling.



Before

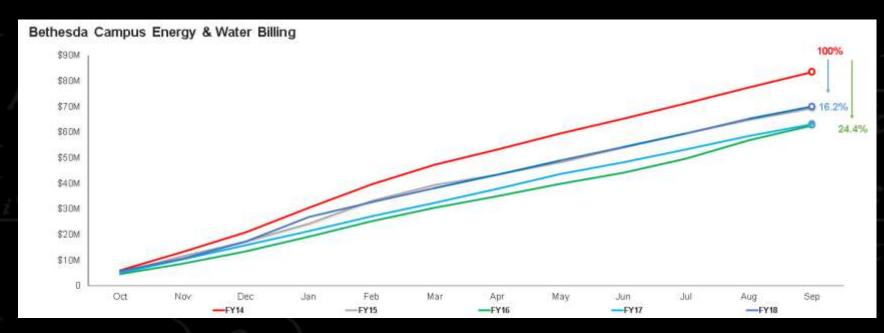
2/

Real-time Data Quality Dashboard



Tangible Results – Financial

Millions of dollars saved despite increased utility costs & demand!



Thank You

Many thanks to NIH Office of Research Facilities Director Mr. Dan Wheeland, Division of Technical Resources (DTR) Director Dr. Farhad Memarzadeh, Deputy Director Mrs. Alamelu Ramesh, and colleagues in DTR team to make all of these happen!

Contact Information

Don Guan Ph.D. P.E. don.guan@nih.gov Chief, Utilities Engineering Branch Division of Technical Resources Alex Huang
alex.huang@nih.gov
Mechanical Engineer
Utilities Engineering Branch
Division of Technical Resources

Kayvan Torkashvan

kayvan.torkashvan@nih.gov General Engineer Utilities Engineering Branch

Division of Technical Resources

Data Generation

Energy Balance

Energy In = Energy Out
$$Q_{In} + W_{in} = Q_{out}$$

$$Tons_{Evap} + kW = Tons_{Cond}$$

$$Percent = \frac{Tons_{Evap} * Conversion + kW}{Tons_{Cond} * Conversion} * 100$$

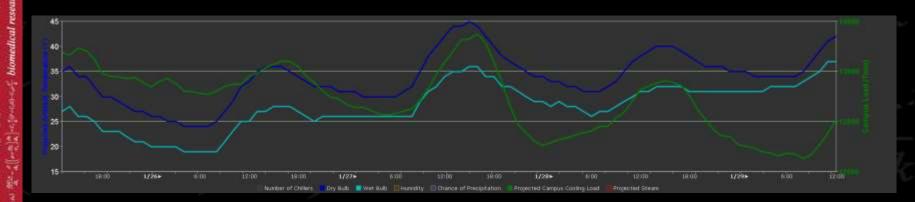
Error Propagation

$$\begin{split} kW &= \sqrt{3} * V * I * PF \\ \frac{\partial kW}{\partial V} &= \sqrt{3} * I * PF \\ \frac{\partial kW}{\partial I} &= \sqrt{3} * V * PF \\ \frac{\partial kW}{\partial PF} &= \sqrt{3} * V * I \\ W &= \dot{m}(h_i - h_e) * Conversion \end{split}$$

 h_i = enthalpy at Steam Turbine Inlet at Saturation h_e = enthalpy at Surface Condenser Vacuum Pressure

$$\begin{split} s_{i,Compressor} &= \sqrt{\left(\frac{\partial W}{\partial m}\right)^2 s_m^2 + \left(\frac{\partial W}{\partial h_i}\right)^2 s_{h_i}^2 + \left(\frac{\partial W}{\partial h_e}\right)^2 s_{h_e}^2} + Conversion^2 \\ s_{i,Cdw\;Pump} &= \sqrt{\left(\frac{\partial kW}{\partial V}\right)^2 s_V^2 + \left(\frac{\partial kW}{\partial I}\right)^2 s_I^2 + \left(\frac{\partial kW}{\partial PF}\right)^2 s_{PF}^2} \\ s_{i,Chw\;Pump} &= \sqrt{\left(\frac{\partial kW}{\partial V}\right)^2 s_V^2 + \left(\frac{\partial kW}{\partial I}\right)^2 s_I^2 + \left(\frac{\partial kW}{\partial PF}\right)^2 s_{PF}^2} \\ s_{i,CT\;Pump} &= \sqrt{\left(\frac{\partial kW}{\partial V}\right)^2 s_V^2 + \left(\frac{\partial kW}{\partial I}\right)^2 s_I^2 + \left(\frac{\partial kW}{\partial PF}\right)^2 s_{PF}^2} \\ s_{i,KW} &= \sqrt{s_{Compressor}^2 + s_{Chw\;Pump}^2 + s_{Cdw\;Pump}^2 + s_{CT}^2} \end{split}$$

Machine Learning Models Learning



- Model learned cooling load vs. ambient lead/lag effect
- Learned using data with no explicit context
- Took several years worth of data to recognize pattern
- Data provided insight on system dynamics with respect to weekend/weekday, time lag between ambient heat and cooling load, increase in demand for steam on weekdays around 8am and 5pm