

Forecasting and Dynamic Real-Time Optimization of a Campus District Energy System using PI

Dr. Kody Powell and Dr. Pratt Rogers



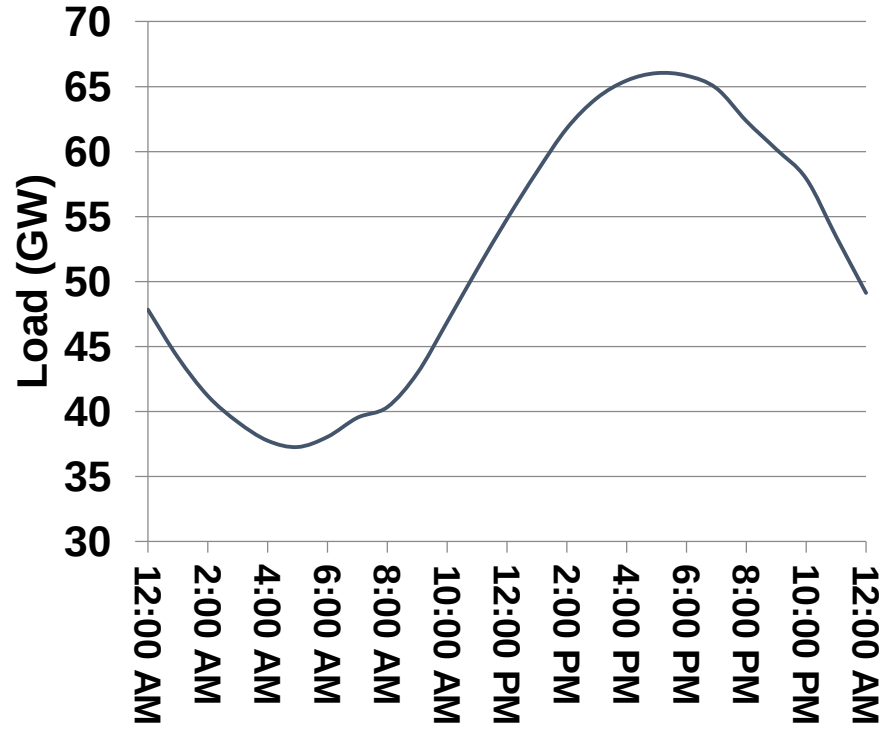
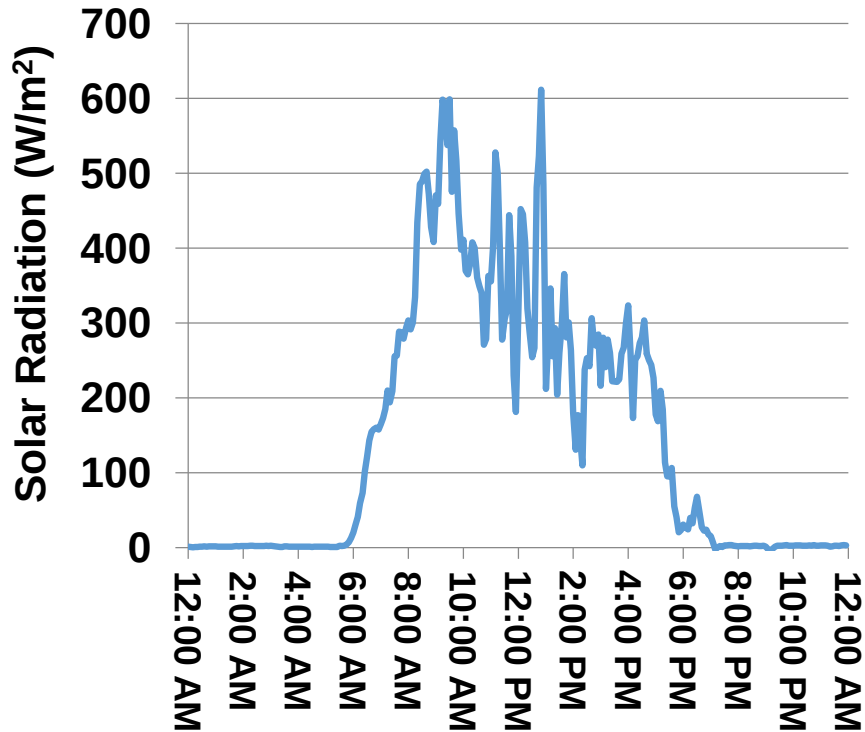
About Me: Kody Powell, Ph.D.

- University of Utah – Dept. of Chemical Engineering
 - Previously ExxonMobil Research and Engineering
- Automation and Optimization **Researcher**
- Research focus on energy systems and smart grid
 - Solar energy
 - Distributed energy
 - Manufacturing/process systems
 - Building energy management
 - **Energy Storage**
- My goals as a professor and researcher
 - Develop technology for systems to be “smarter”
 - Develop engineers with applicable skill sets for the market
- Warning: I am a PI novice

About Me: Pratt Rogers, Ph.D.

- University of Utah – Dept. of Mining Engineering
 - Previously MISOM Technologies
- Analytics and Operations Engineering **Researcher**
- Research focus on
 - Socio-technical systems: people, processes, technology
 - Machine learning and analytics nexus
 - Management safety and production systems
- My goals as a professor and researcher
 - Operationalize cool technology
 - Develop engineers with applicable skill sets for the market

The Fundamental Problem



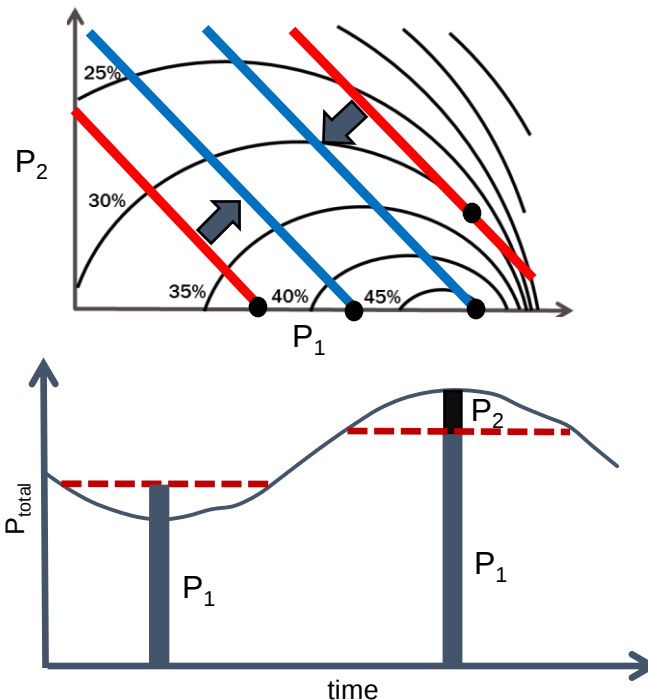
The Solution(s)

- Energy Storage
 - Large scale
 - Heavy lifter
 - Distributed
 - Thermal Energy storage
 - “Heat things up and cool them down”
- Intelligent Systems
 - Powerful can be smart too

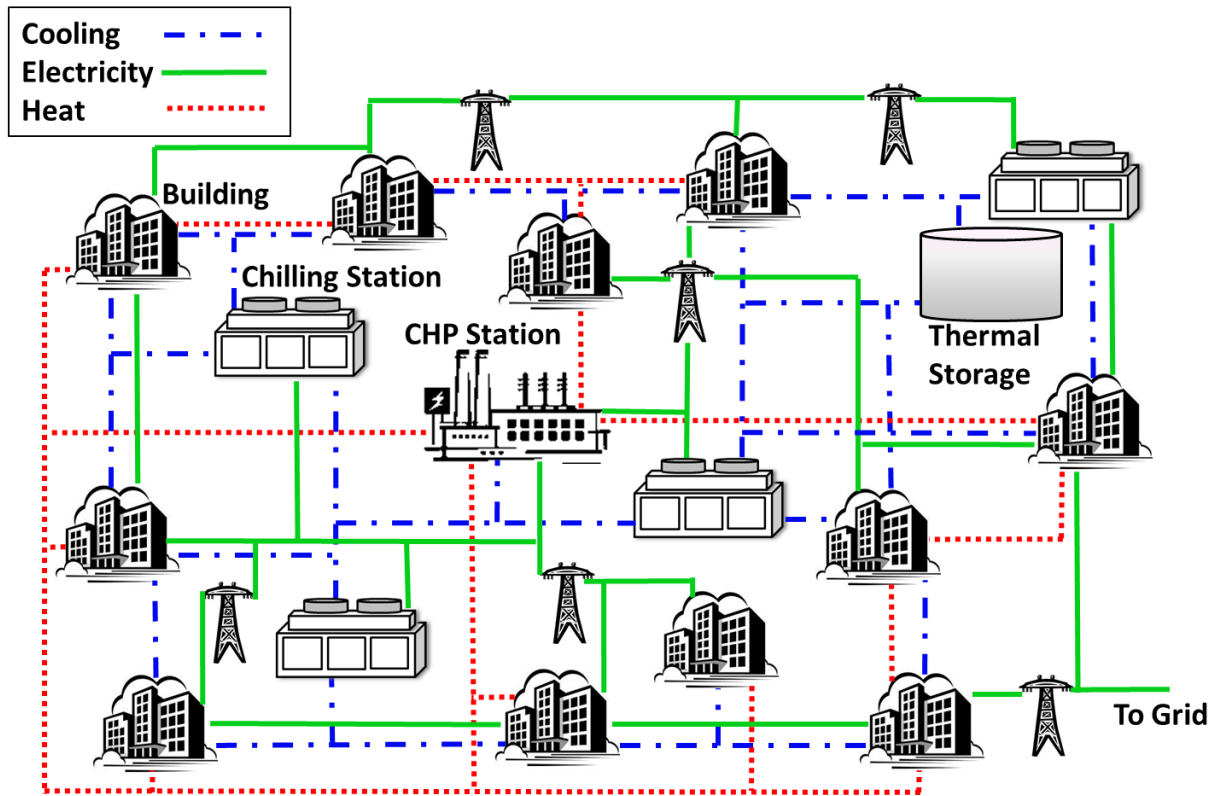


Smart Energy Storage

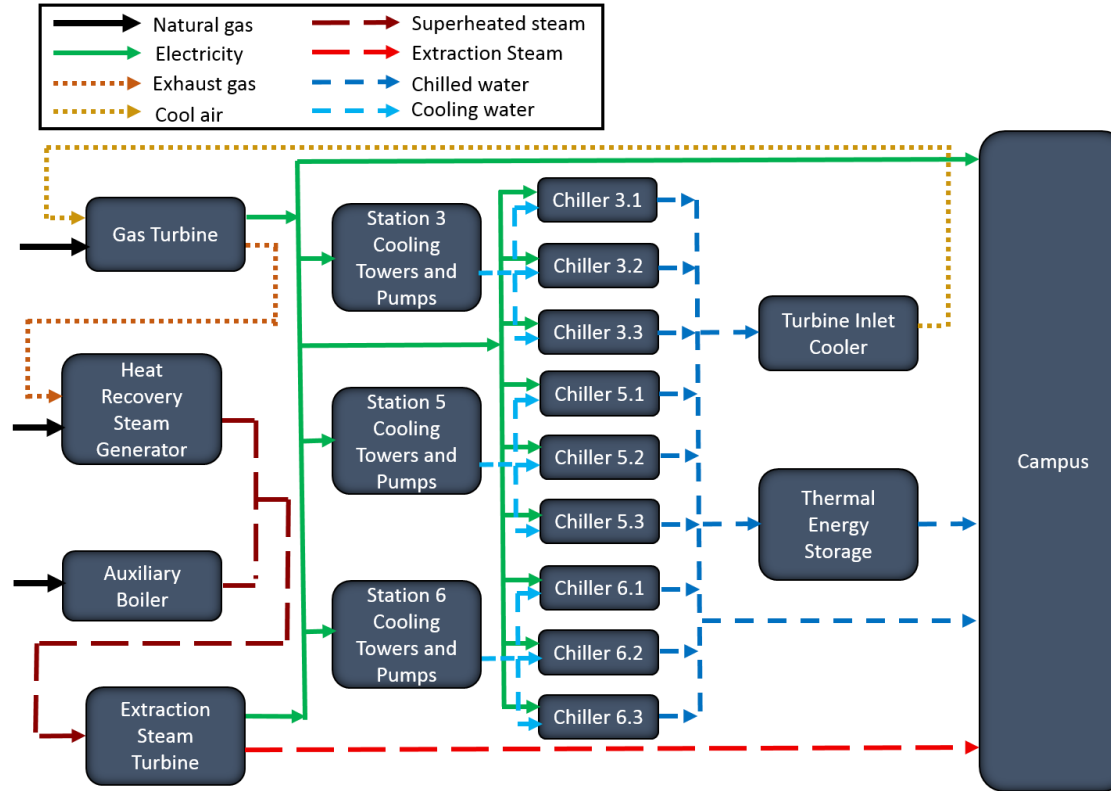
- Constraints
 - $P_1 + P_2 = P_{\text{total}}$
 - $\text{DOF} = 1$
- Dynamic optimization
 - $\text{DOF} = \text{infinite}$
 - Discretize
 - Flexibility
 - Blessing and curse of dimensionality



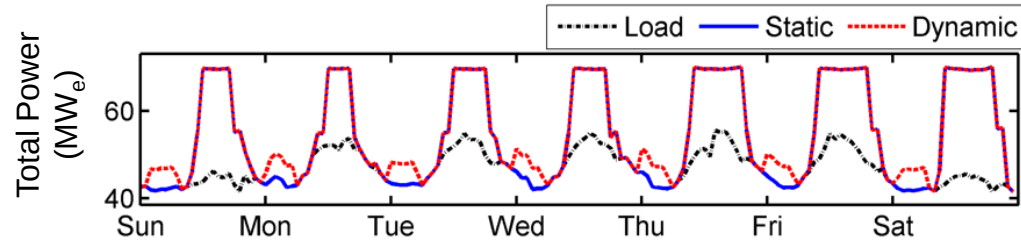
Energy System Optimization



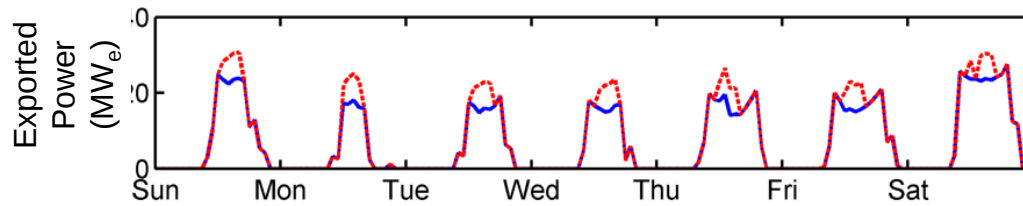
Complete System Model



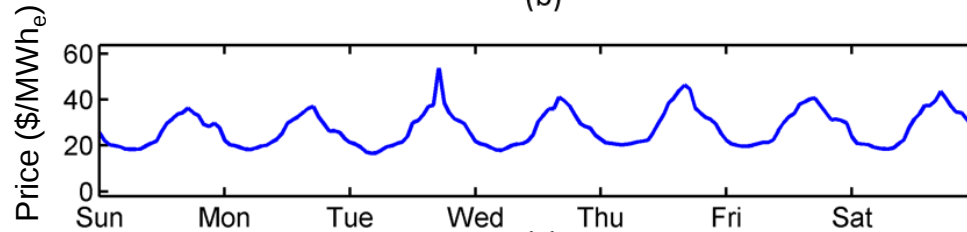
Results: Grid Interconnection Example



(a)



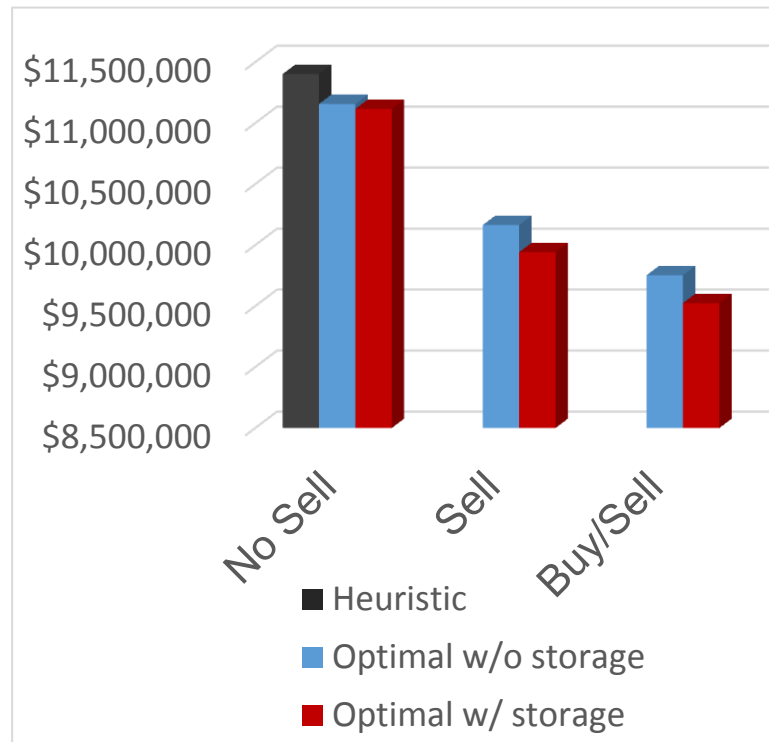
(b)



(c)

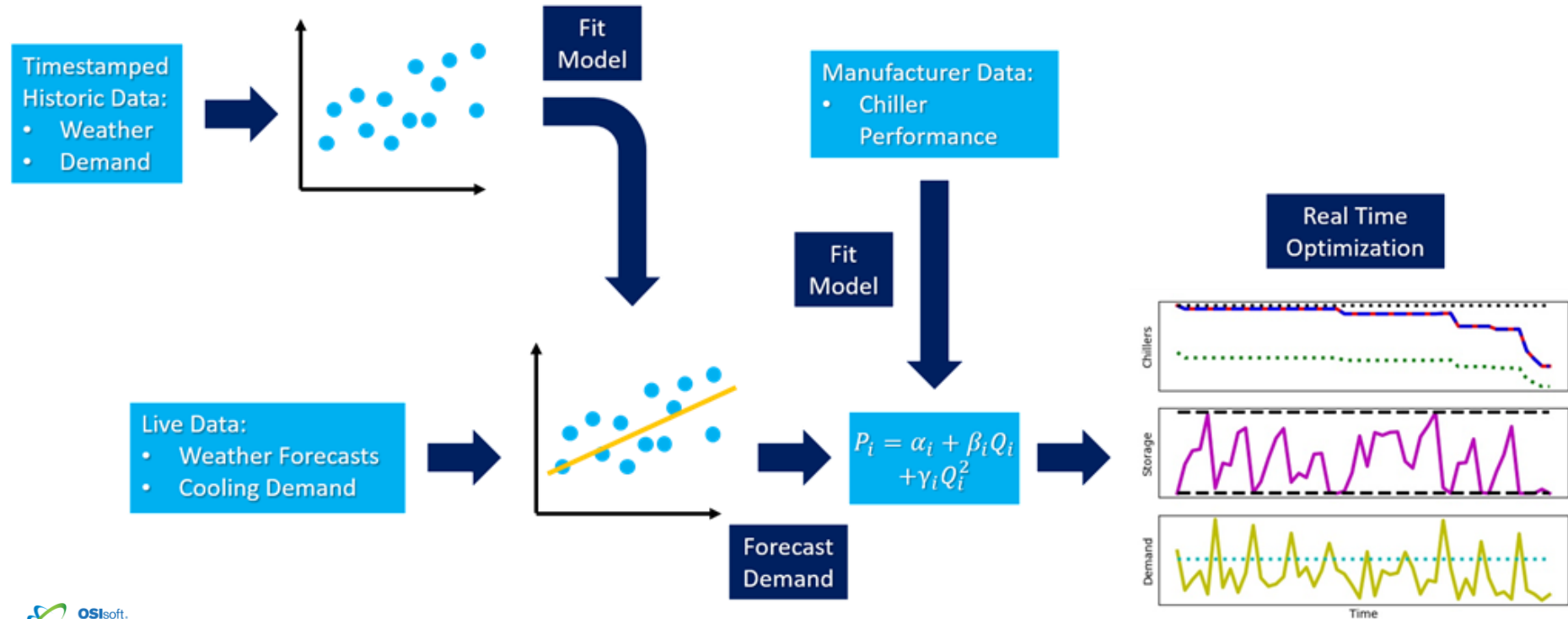
Summary of Results

- 2.2% savings by optimizing
- Marginal benefit using storage for efficiency
- +6 MW_e peak capacity
- Storage beneficial in market conditions
 - Additional 2.2-2.4% savings
- \$1.9 M (16.5%) savings overall

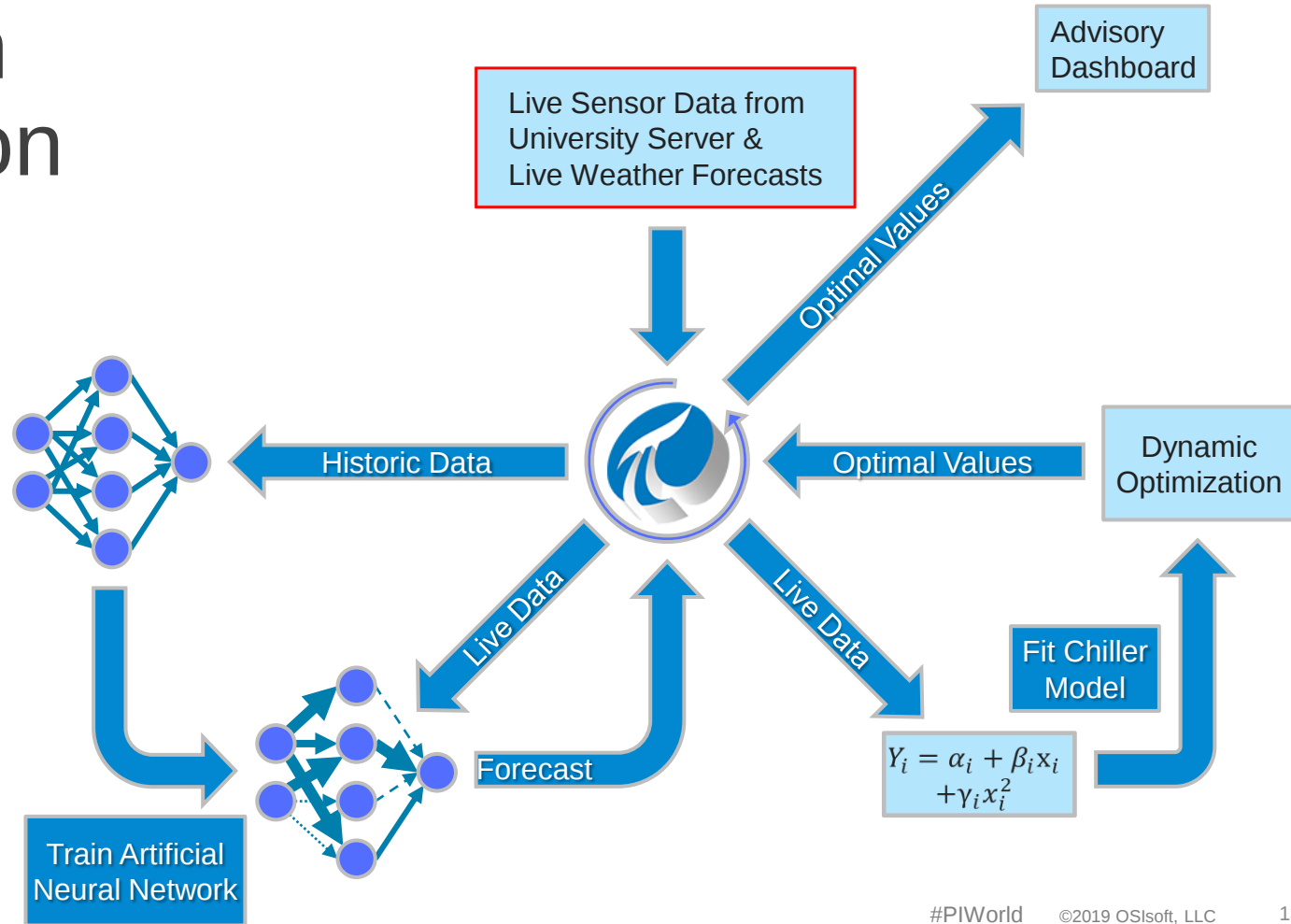


How Do We Make Theoretical Results A Reality?

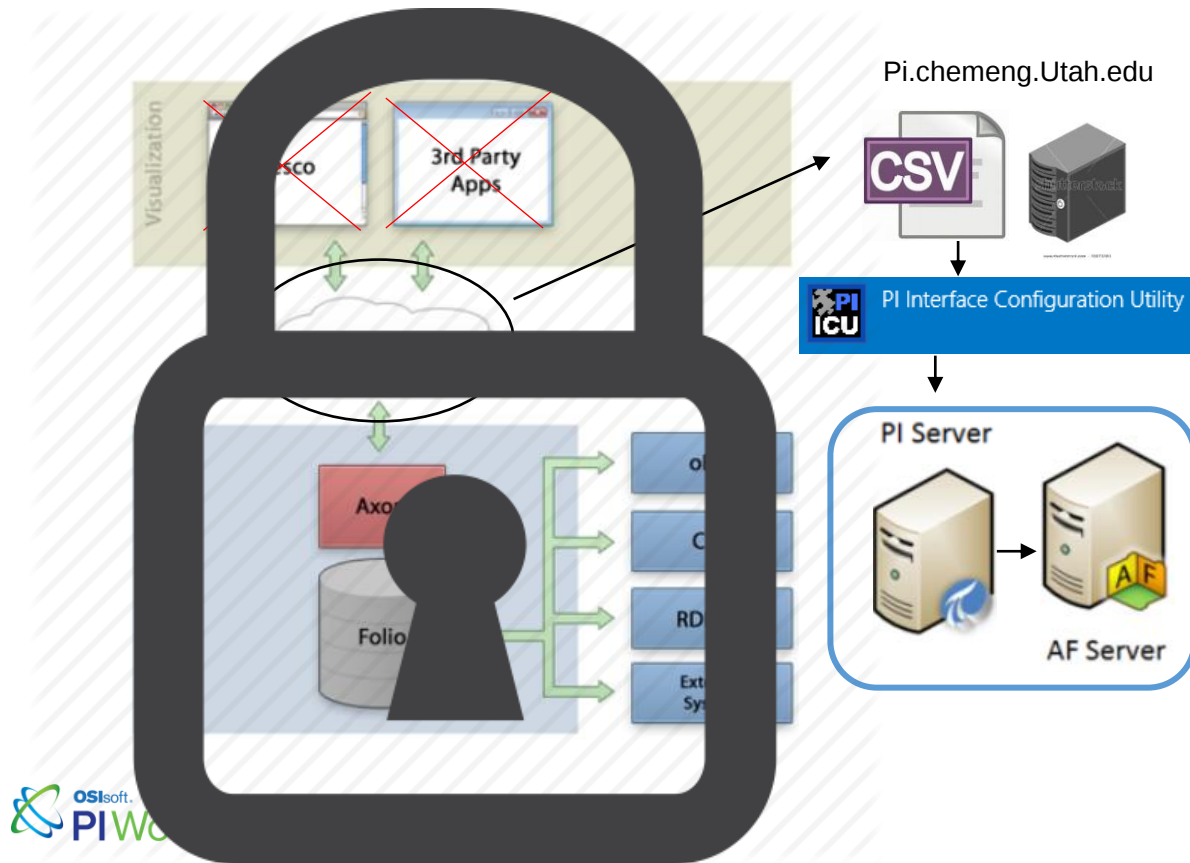
Building an Optimization Application Around PI



Building an Optimization Application around PI



Skyspark PI System Connection



Process & Business Intelligence

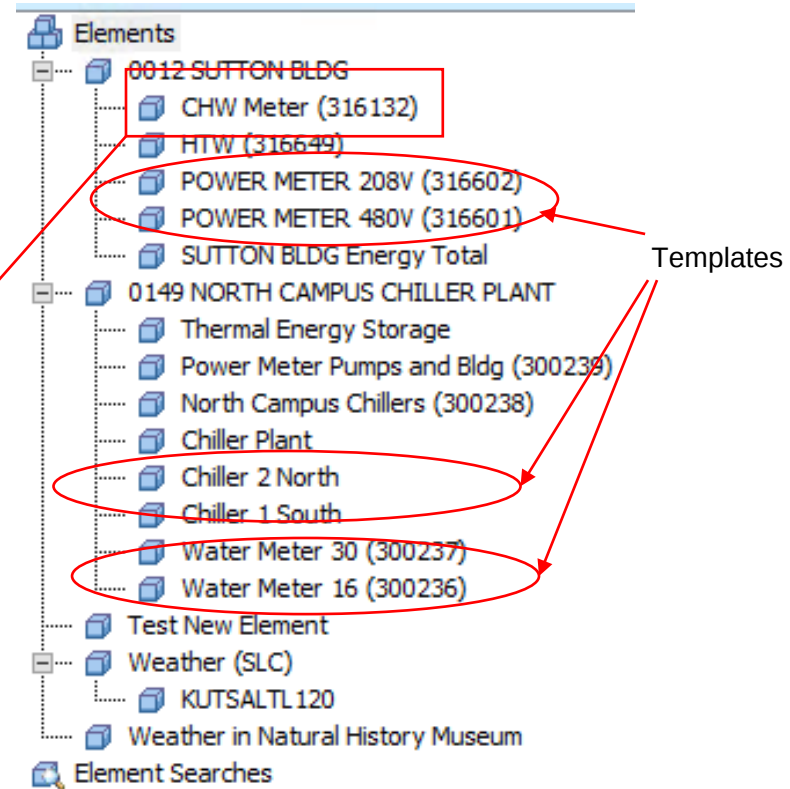


The PI System and current data

- Element Hierarchy – Tree Structure
- All names kept consistent with Haystack Terminology
- Multiple Attributes for each Element
- Templates
- Tags

Current Day Total_b	16636928
Daily Energy Value_a	22678016 Btu
Energy Month Total	6598860 Btu
Energy Rate	0 Btu/h
Energy Total Mode 1	5.94393E+09 Btu
Energy Total Mode 1 Status	OK
Five day avg_c	23703244.8 Btu
Return Temperature	53.94992 °F
Supply Temperature	53.94501 °F

Tag for each data source

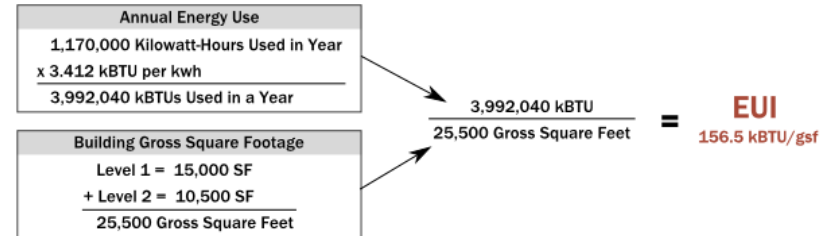


Advanced calculations in PI AF

Calculating a Building's EUI

A school contains a main floor consisting of 15,000 square feet, a second floor consisting of 10,500 square feet. The school used 1,170,000 kilowatt-hours of power during the year in question. Kilowatt-hours is multiplied by 3.412 to obtain kBTUs, therefore $1,170,000 \times 3.412 = 3,992,040$ kBTUs. This is divided by the total square footage of 25,500 square feet for an Energy Use Intensity of $3,992,040 / 22,500 = 156.5$ kBTU/sf.

Using PI Unit Conversions to Measure Energy Use Intensity (EUI)



<https://www.archtoolbox.com/materials-systems/sustainability/energy-use-intensity.html>

Energy					
Filter					
Name	Abbreviation	Class	Origin	Canonical	Reference
British thermal unit	Btu	Energy	Unknown	1055.05585262 J	1055.05585262 J
calorie	cal	Energy	Unknown	4.1868 J	4.1868 J
EUI	kBtu/Ft2	Energy	Unknown		Btu = (1000*91000/365) * EUI, kBtu/Ft2 = Btu / (1000*91000/365)
gigajoule	GJ	Energy	Unknown	1000000000 J	1000000000 J
gigawatt hour	GWh	Energy	Unknown	3600000000000 J	3600000000000 J
joule	J	Energy	Unknown	1 J	1 J
kilocalorie	kcal	Energy	Unknown	4186.8 J	1000 cal
kilojoule	kJ	Energy	Unknown	1000 J	1000 J
kilowatt hour	kWh	Energy	Unknown	3600000 J	3600000 J
megajoule	MJ	Energy	Unknown	1000000 J	1000000 J
megawatt hour	MWh	Energy	Unknown	3600000000 J	3600000000 J
million British thermal unit	MM Btu	Energy	Unknown	1055055852.62 J	1000000 Btu
million calorie	MMcal	Energy	Unknown	4186800 J	1000000 cal
watt hour	Wh	Energy	Unknown	3600 J	3600 J
watt second	Ws	Energy	Unknown	1 J	1 J

External Data Sources

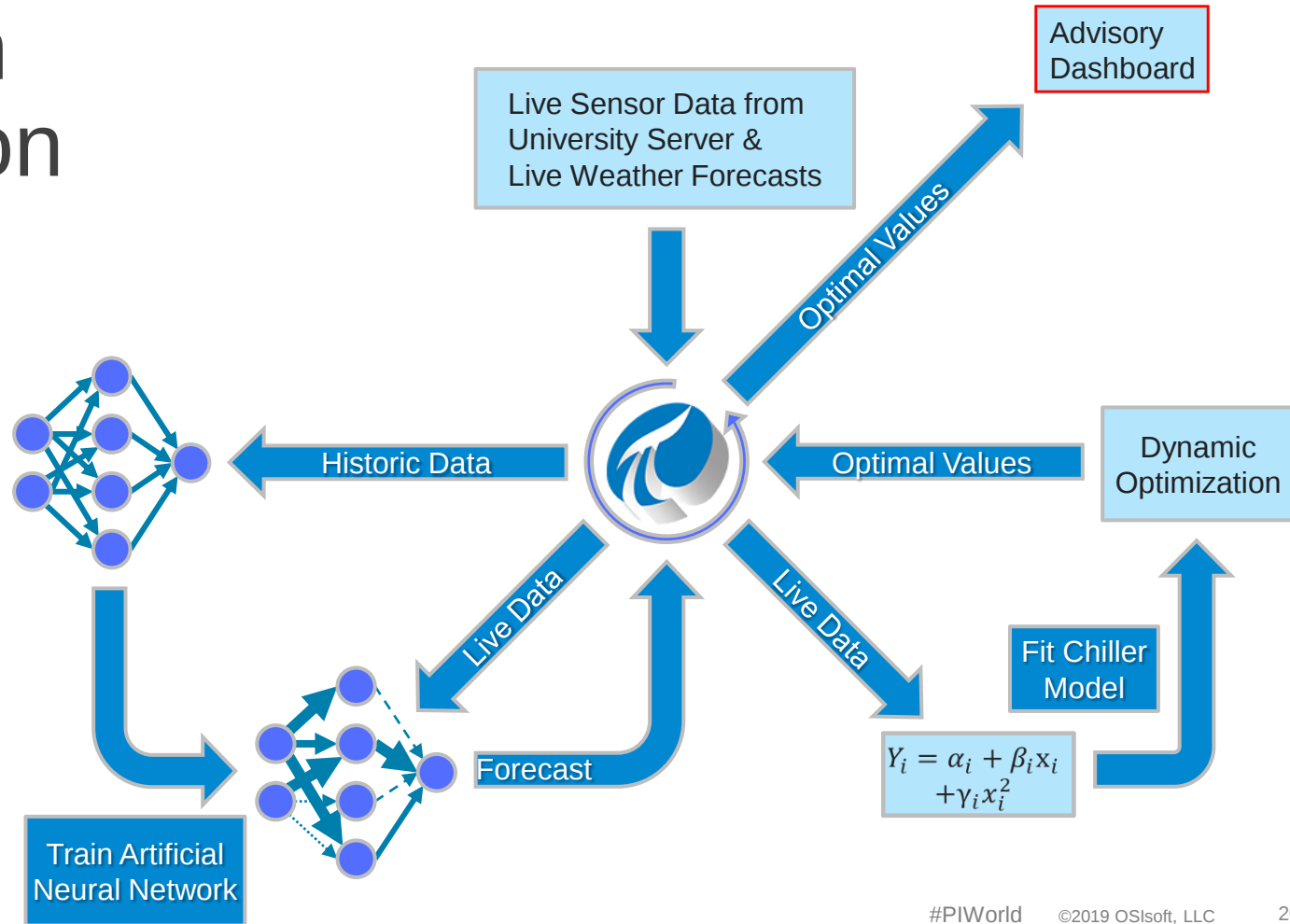


- 3 minute current weather conditions
- Hourly forecasts
- Heating Degree Days



- Forecasted Electricity demand for the region
- Current electric demand for the region
- Current air pollution (PM2.5, O₃, NO₂, & CO)

Building an Optimization Application around PI



Data Analytics – Visualizing EUI



FASB Energy Usage

Energy Used this year
9,008.5 kWh

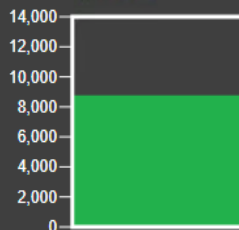
5-Day Avg EUI (Annual Rate)

178.67 kBtu/Ft²

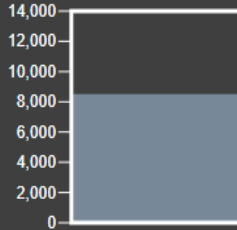


Chilled Water Temp

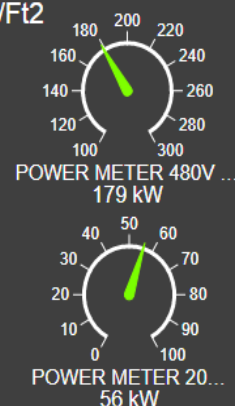
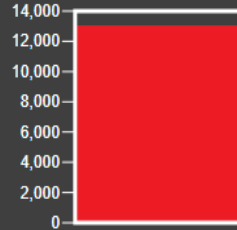
Today's Total
8,771.2 kWh



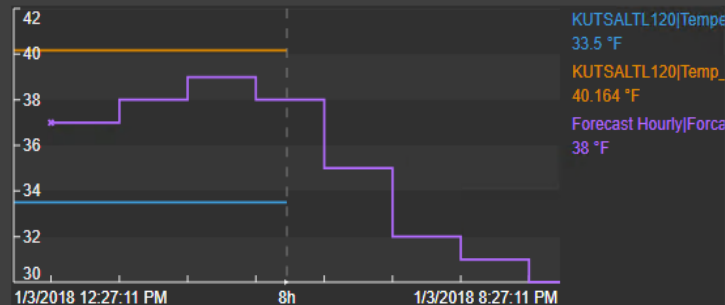
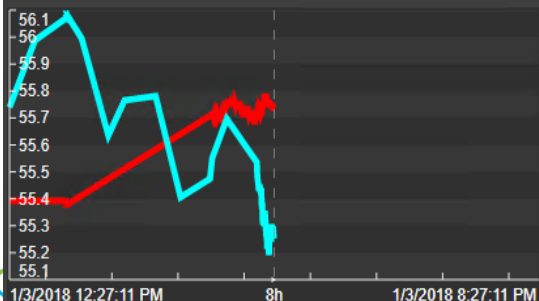
Yesterday at this time
8,514.2 kWh



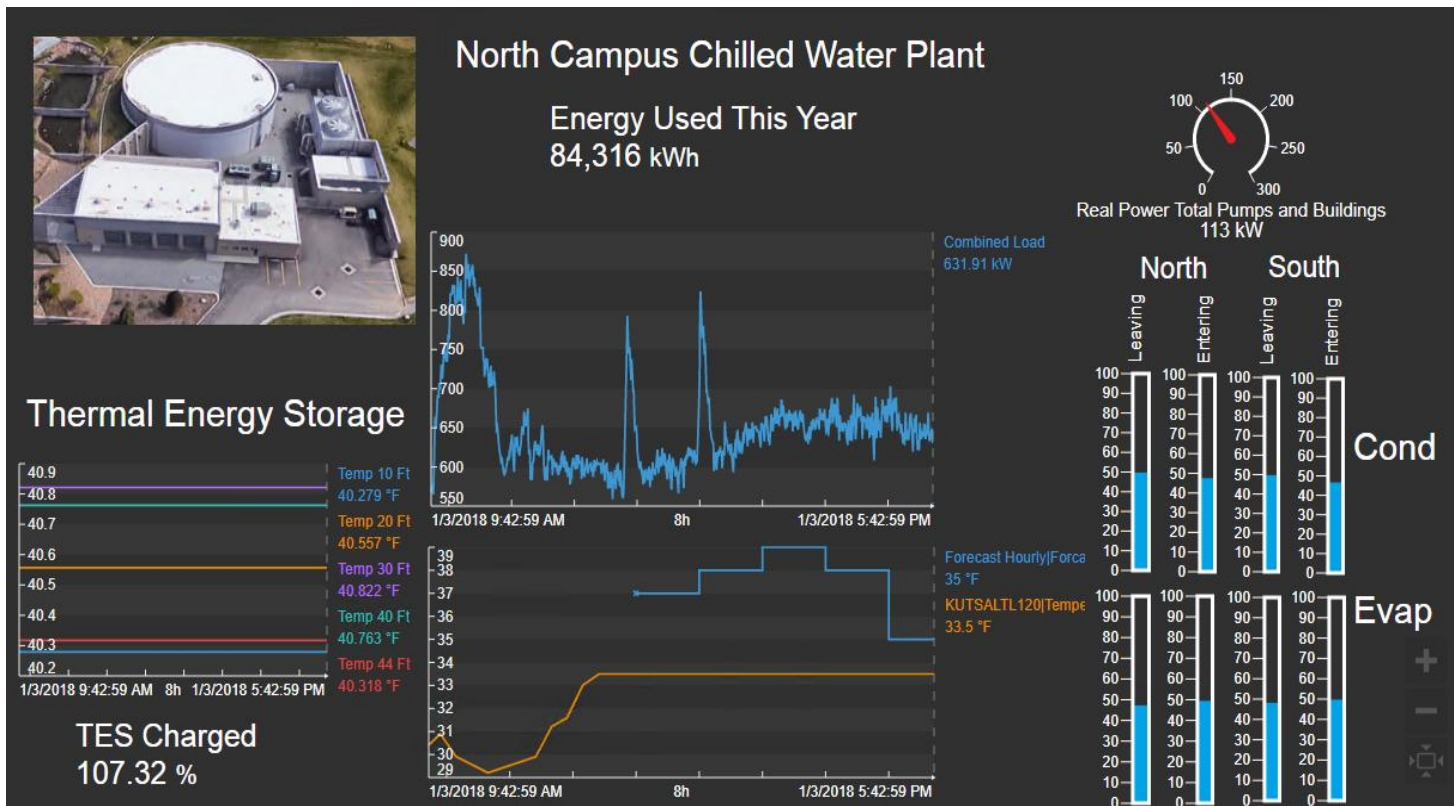
5-Day Avg Total
13,055 kWh



Temperature Today vs. Yesterday



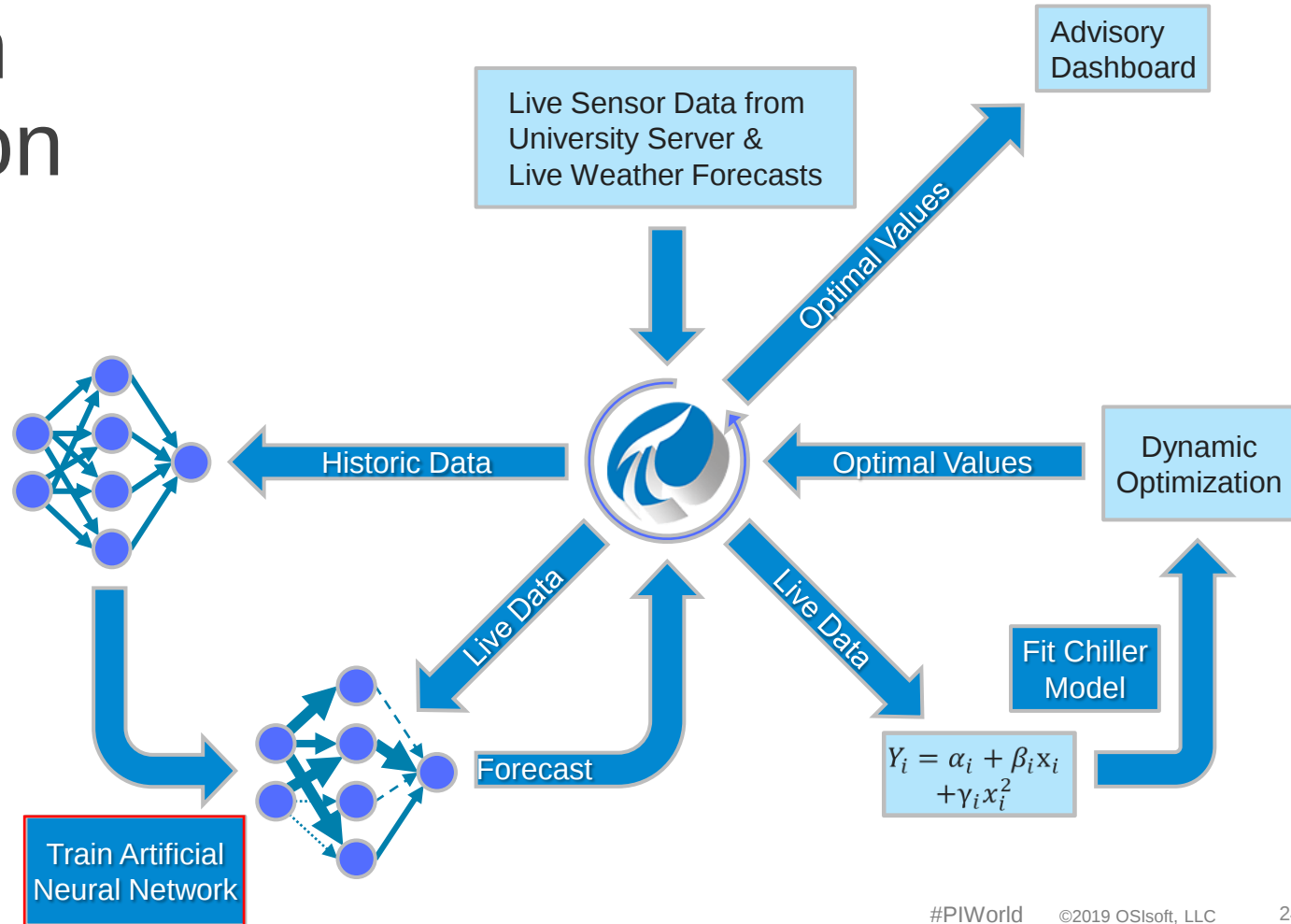
Data Analytics – Visualizing EUI



Analyses

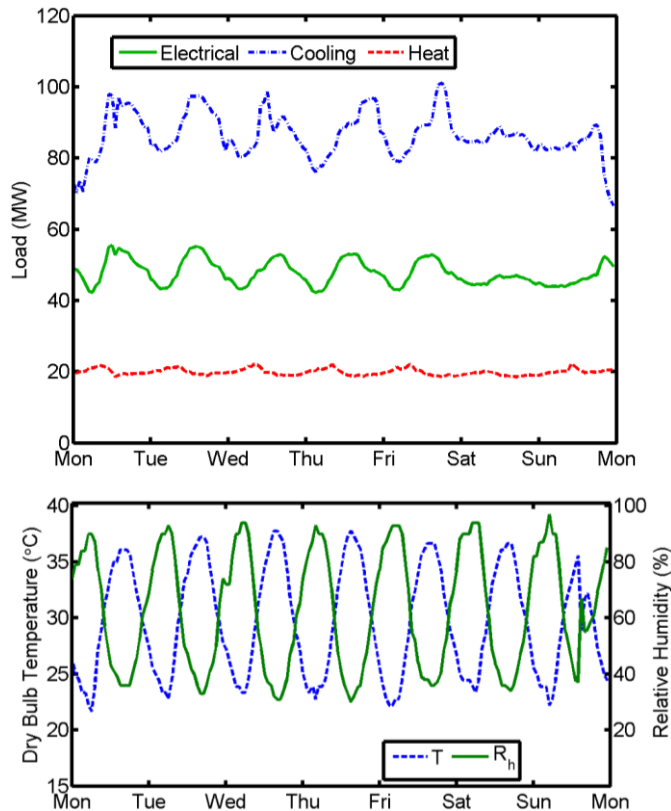
- PI System Analyses – simple
EUI (Annual Rate)
Heating Degree Days
Energy Load
- Python Integration – complex
Dynamic Load Forecasting

Building an Optimization Application around PI

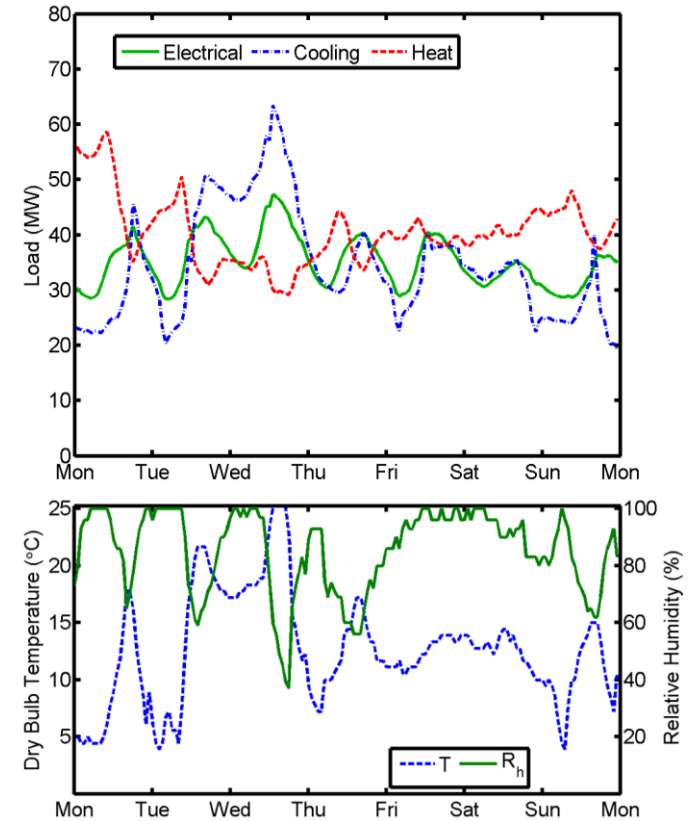


System Loads

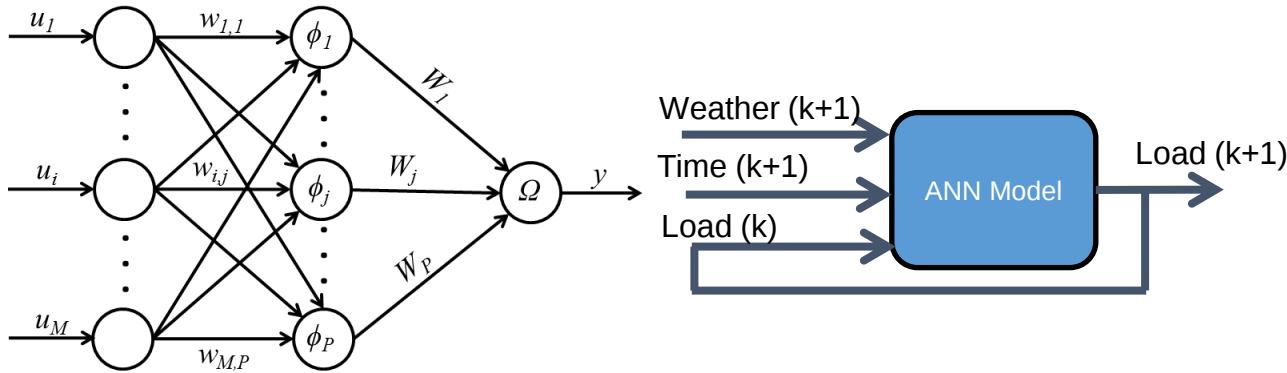
August



February

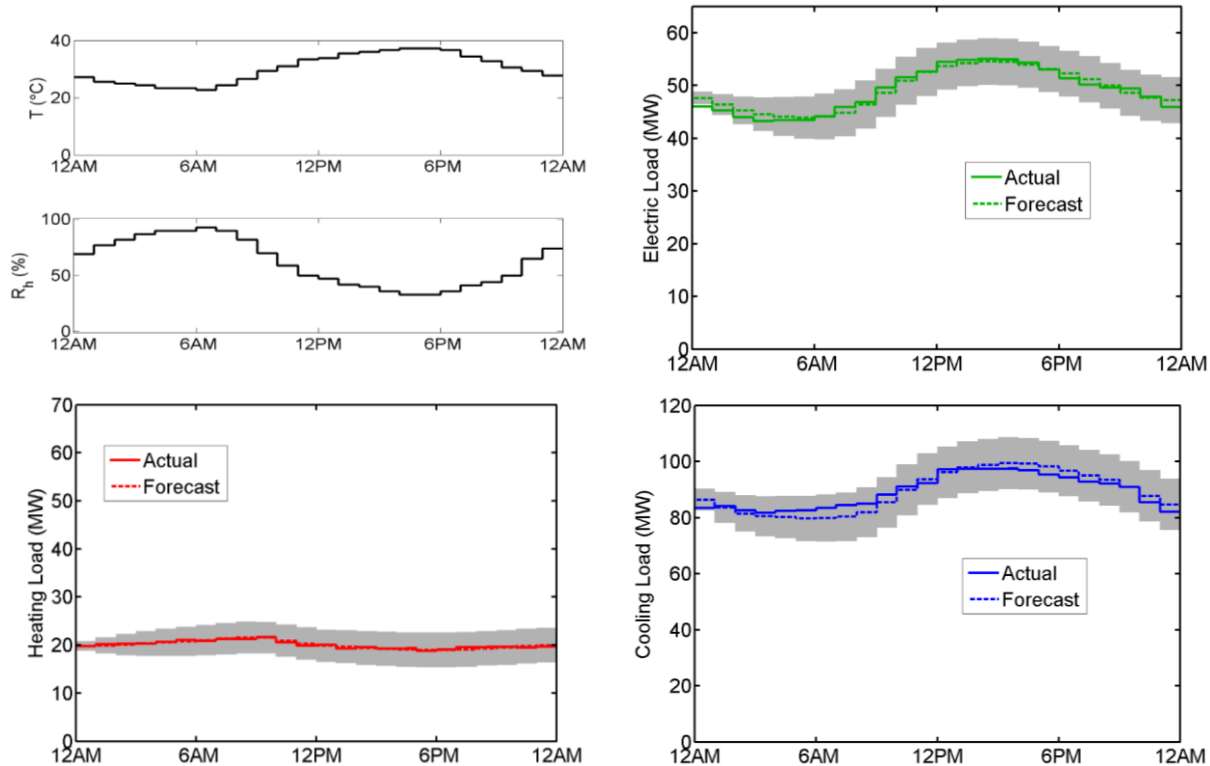


Using AI: Load Forecasting with Recurrent Neural Networks

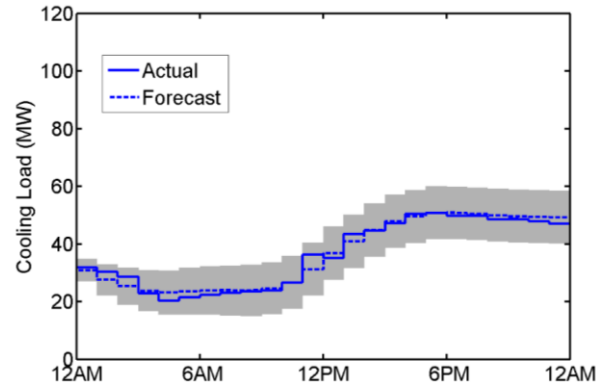
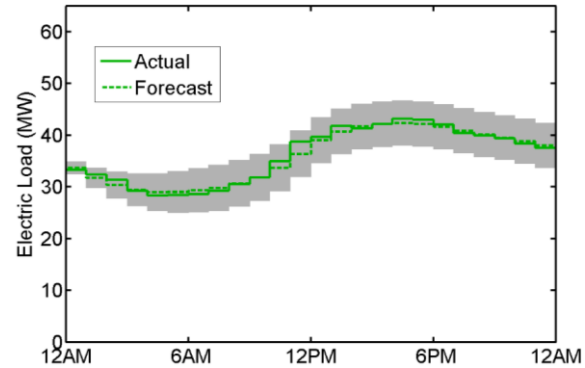
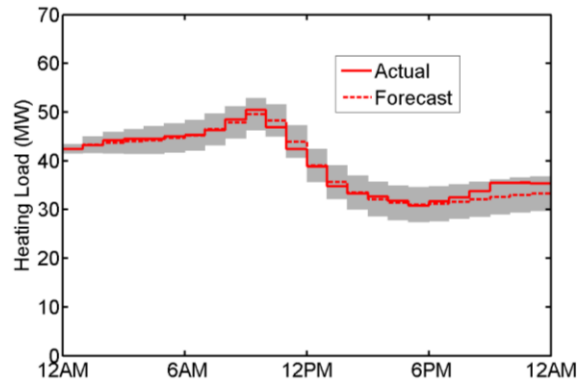
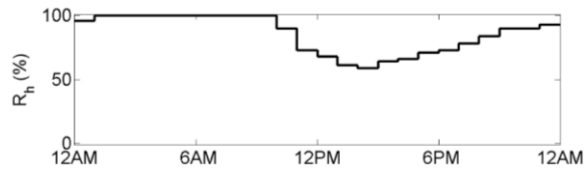
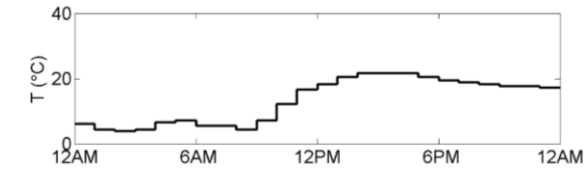


Adjusted R ² values	Cooling	Heating	Electrical
Static Neural Network (weather only)	0.906	0.820	0.808
Static Neural Network (weather and time)	0.945	0.942	0.910
Linear ARX (weather only)	0.911	0.932	0.749
Linear ARX (weather and time)	0.936	0.948	0.850
NARX (weather only)	0.948	0.977	0.864
NARX (weather and time)	0.964	0.986	0.933

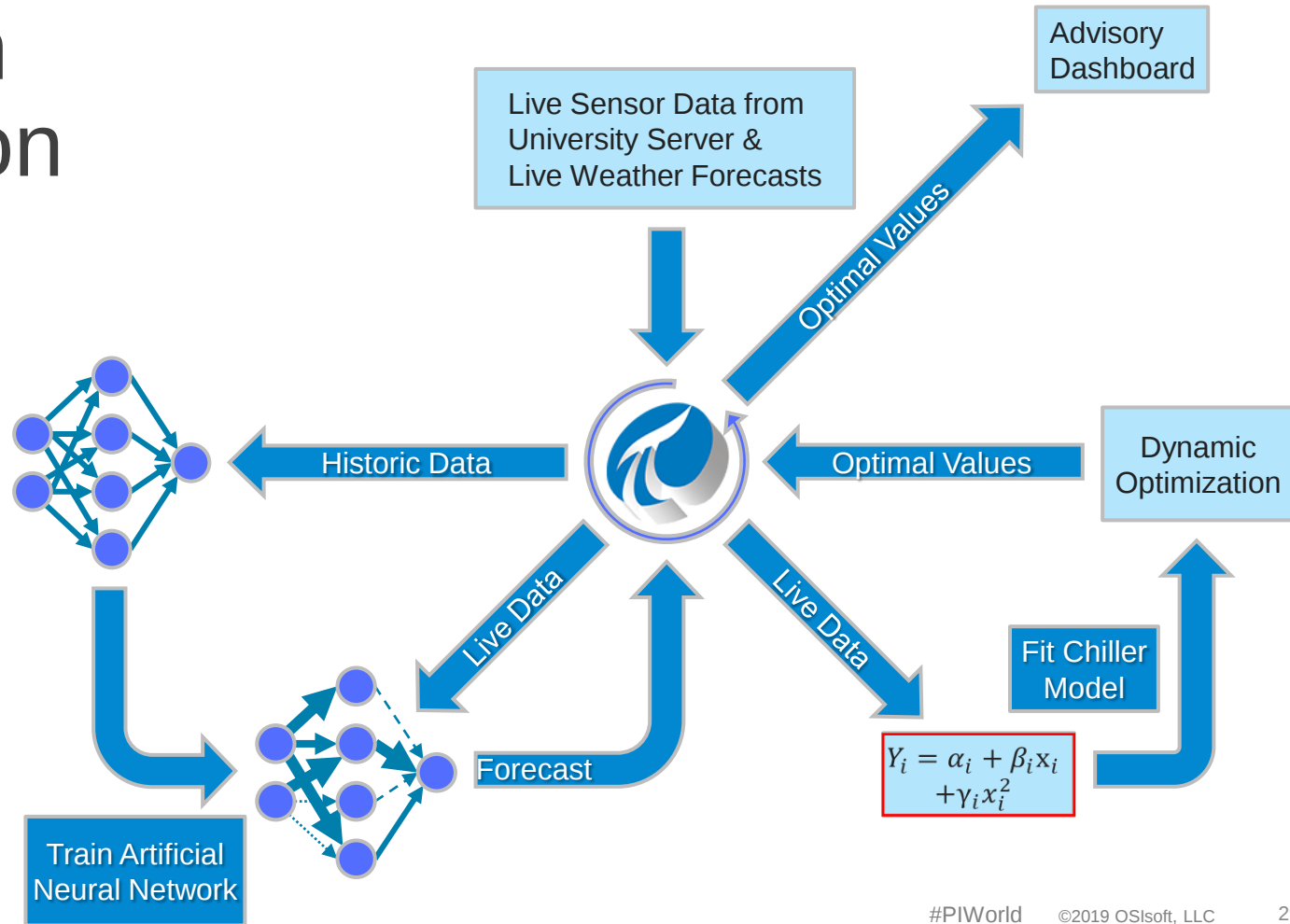
Forecast Results: August



Forecast Results: February

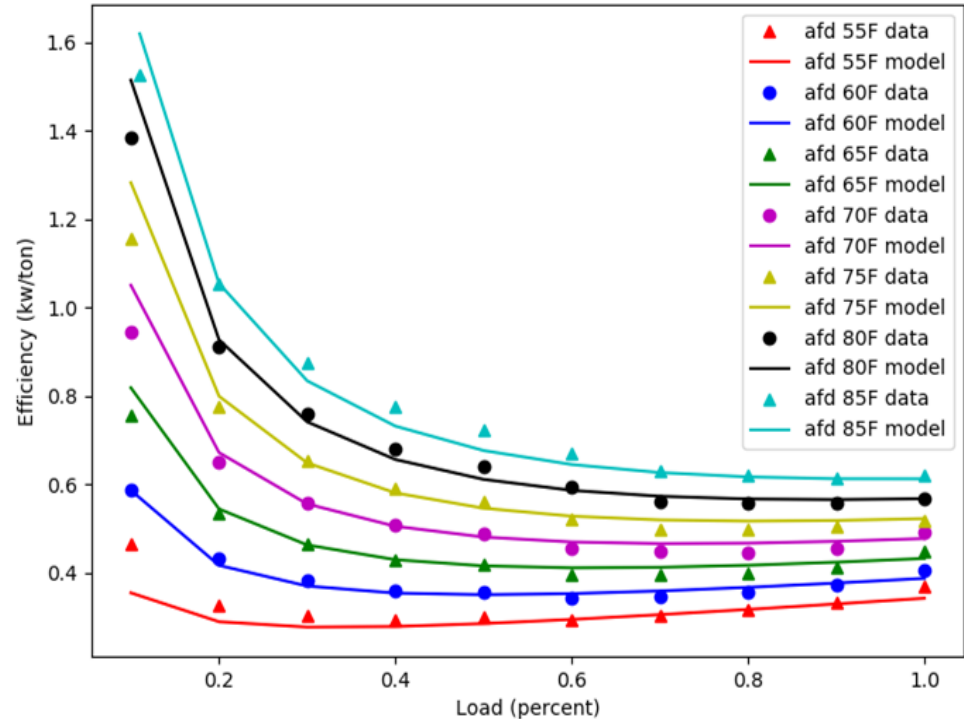


Building an Optimization Application around PI

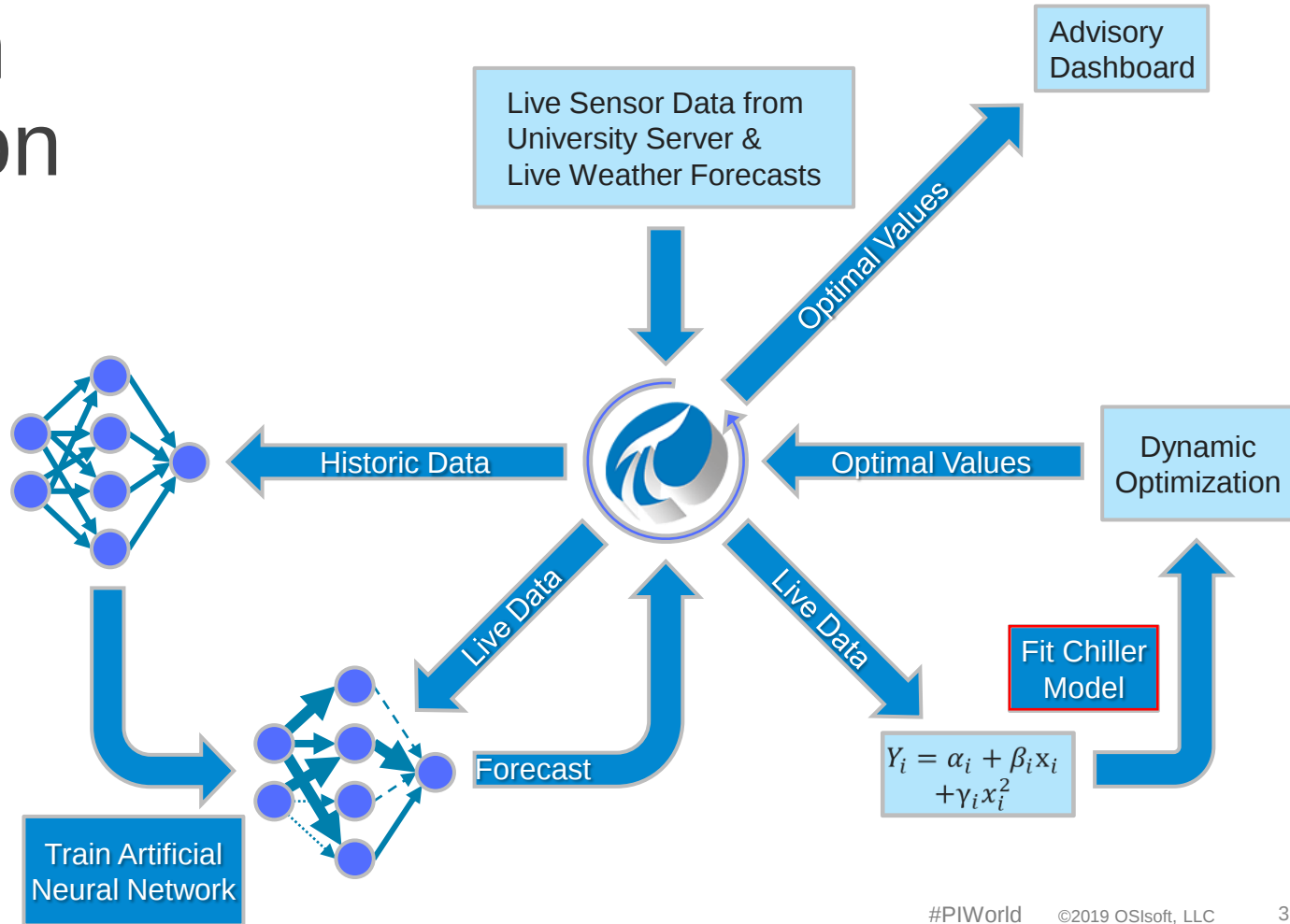


Modeling with Manufacturing Data

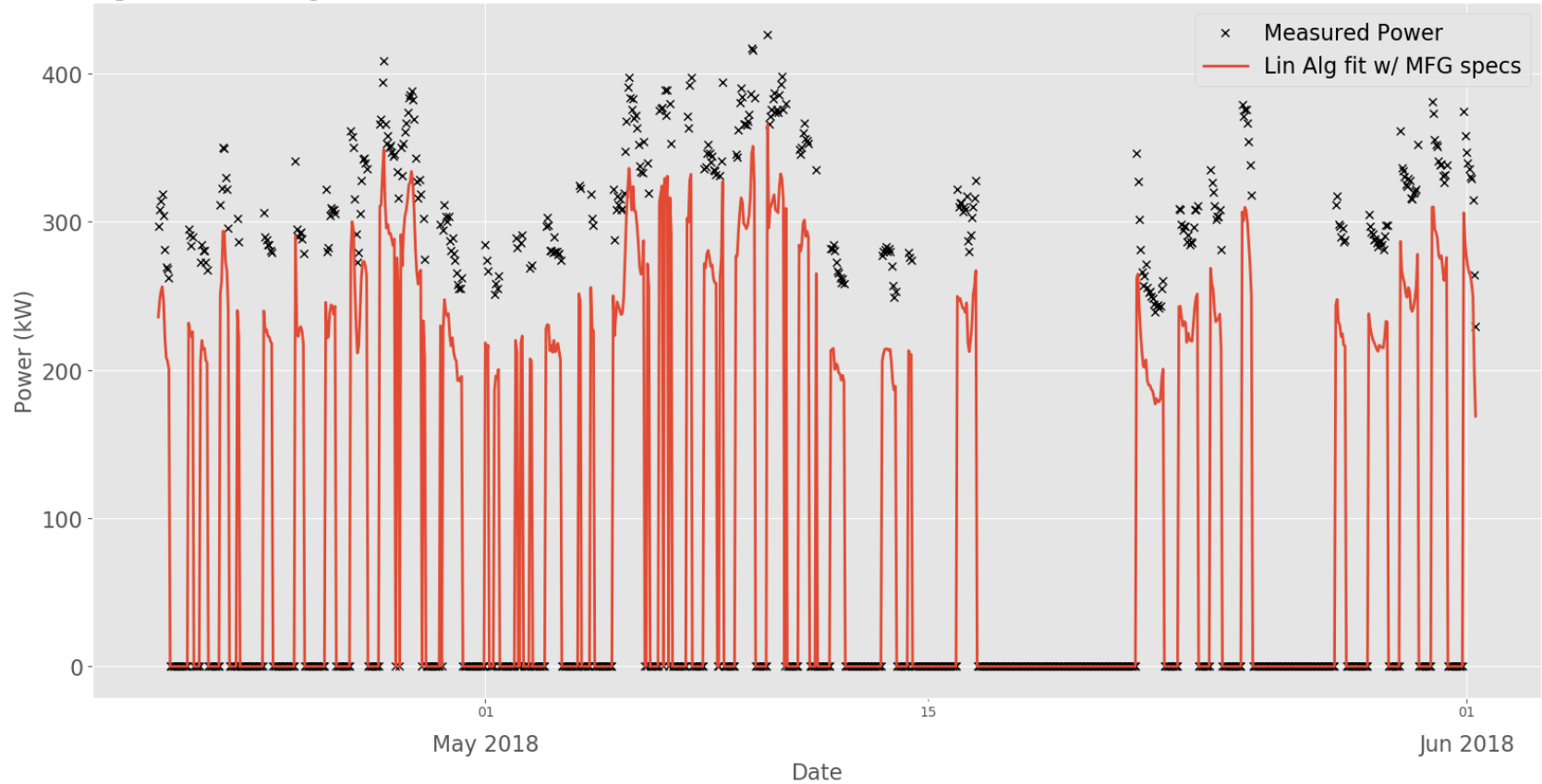
- Need to determine unknown parameters of chiller model generally
- Use data from manufacturer to fit chiller performance
- Put model in quadratic form to speed up optimization



Building an Optimization Application around PI



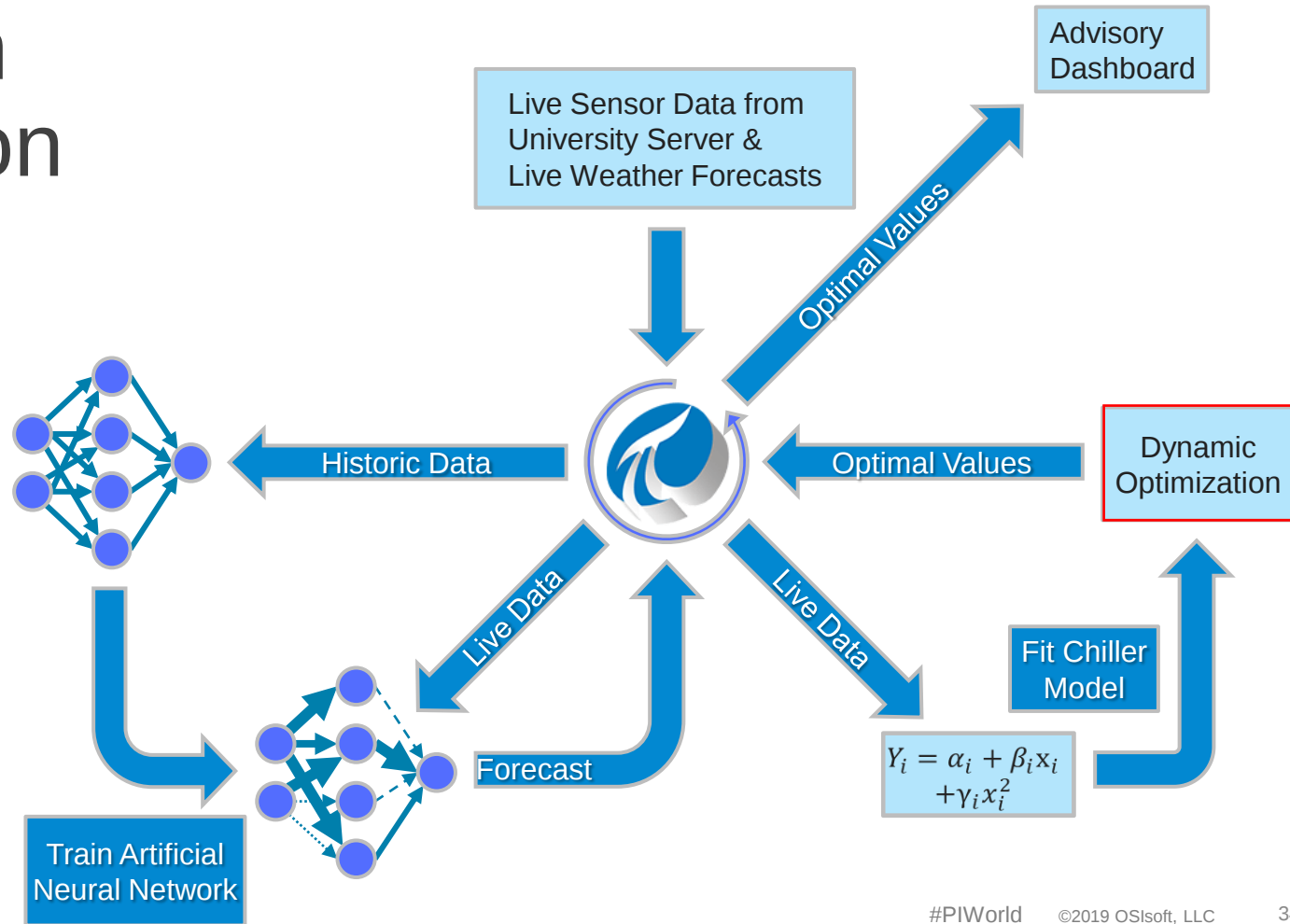
Comparing the Model to PI Data



Dynamic fitting with Moving Horizon Estimation

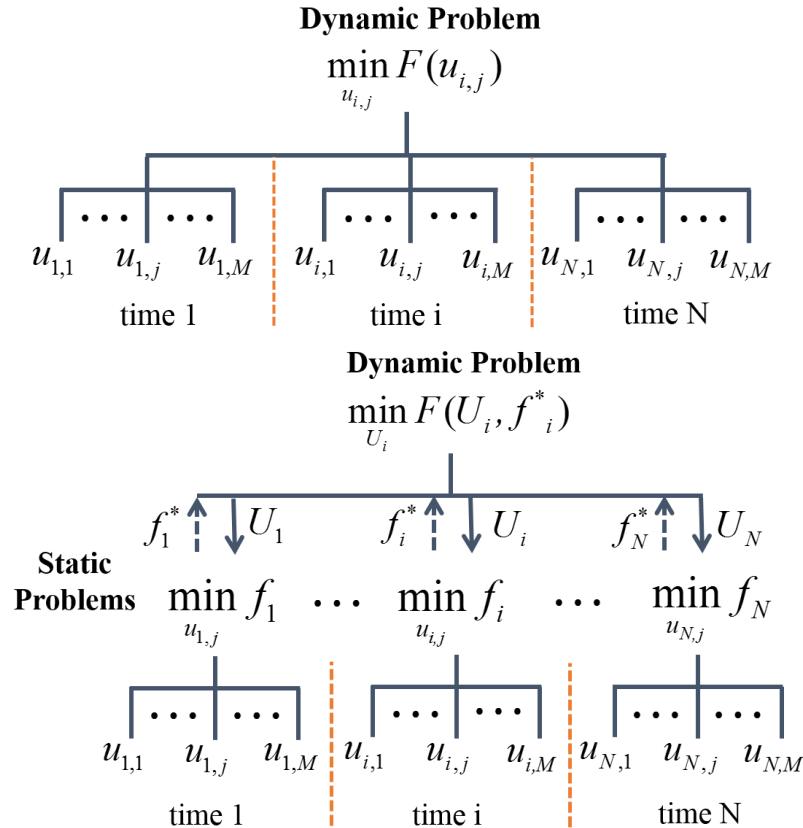


Building an Optimization Application around PI

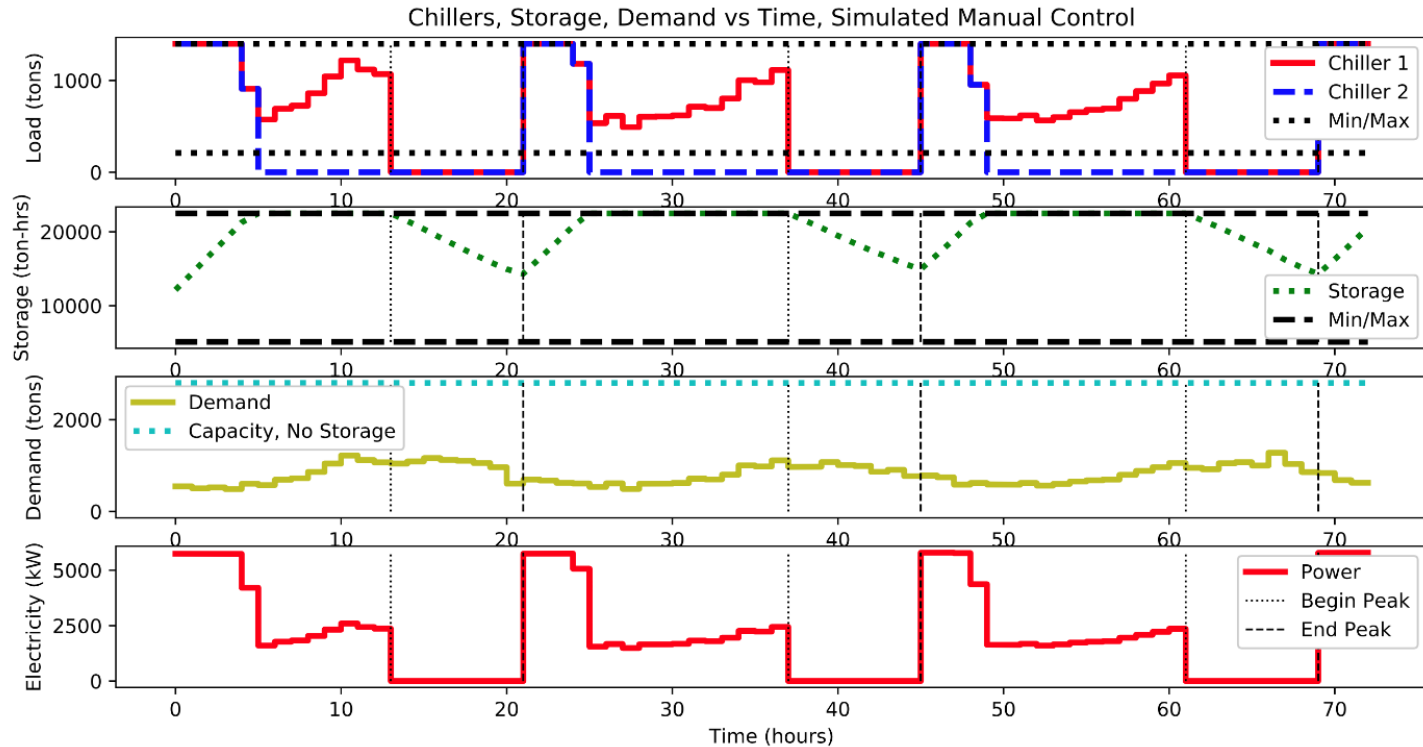


Dynamic Decoupling Approach

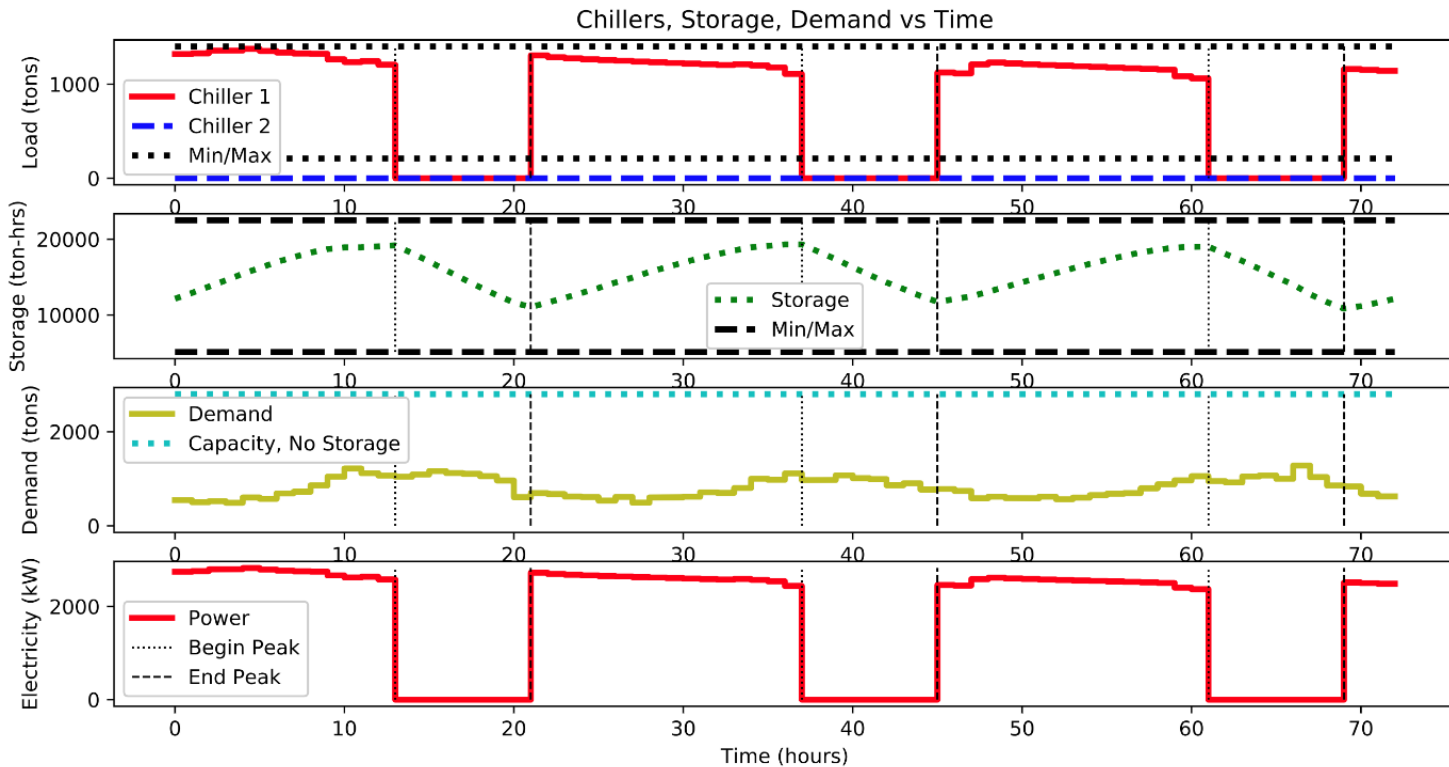
- Combinatorial complexity
- Dynamic problem “guesses” how much energy to store / extract
- Static problems report back
- Back and forth iteration until convergence
- Static problems – MINLPs with convex relaxations
- Static problem solved 1,000-5,000 times



Manual Operation



Dynamically Optimized Operation



Summary of Results

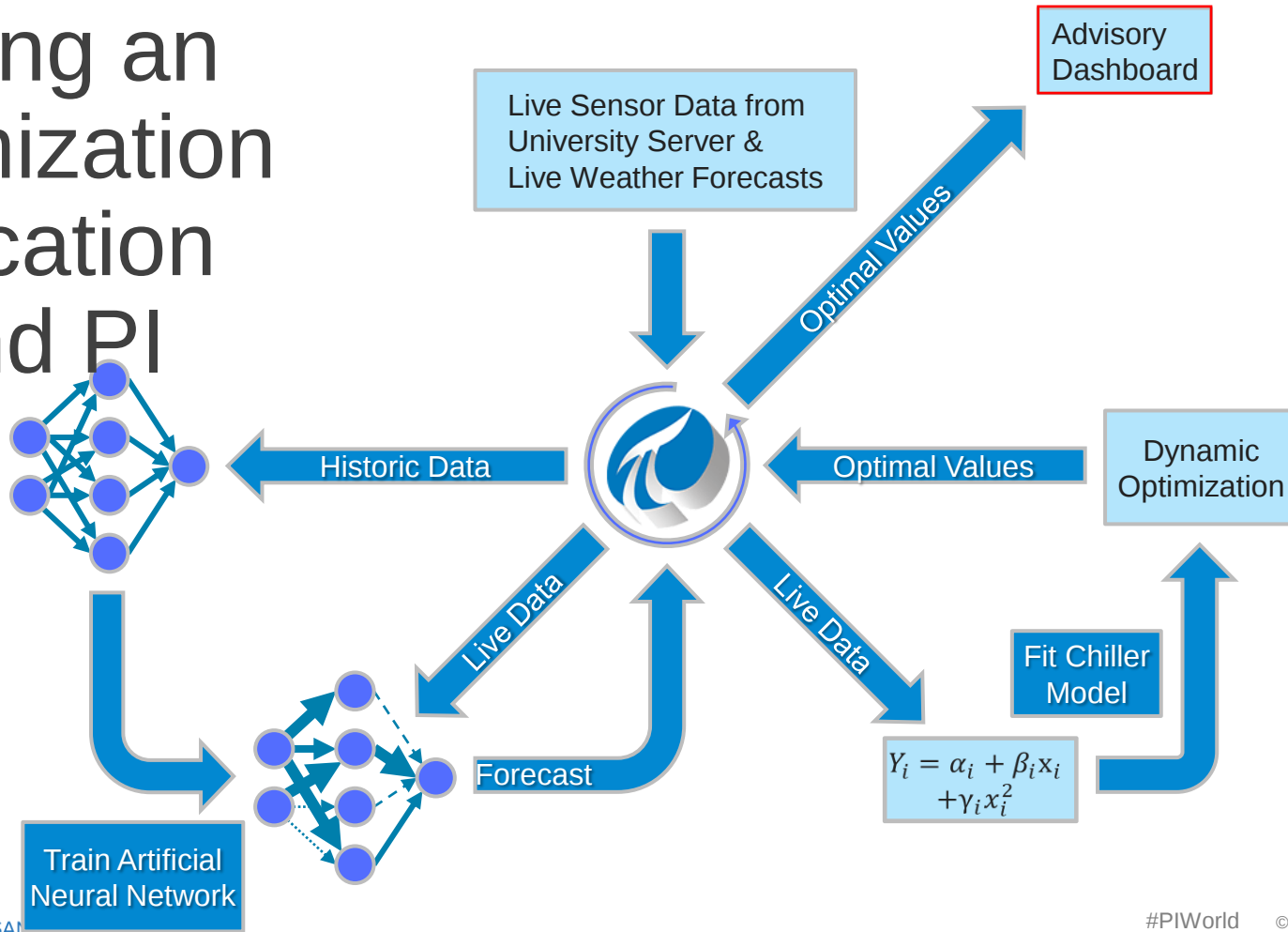
- Dynamic optimization algorithm *predicts 16.5% cost savings*
- Still need to close the loop
 - Make savings a reality

	QPHAC	Manual	BnB
4-h	\$190.30 (0.150 s)	\$246.68 (~ 0 s)	\$165.53 (38 s)
8-h	\$580.89 (0.150 s)	\$632.11 (~ 0 s)	\$557.20 (13 min)
12-h	\$1248.68 (0.167 s)	\$800.55* (~ 0 s)	\$961.61 (24 min)
24-h	\$871.63 (0.150 s)	\$1314.80 (~ 0 s)	Did not converge [†]
72-h	\$4257.48 (0.184 s)	\$5097.72 (~ 0 s)	Did not converge [†]

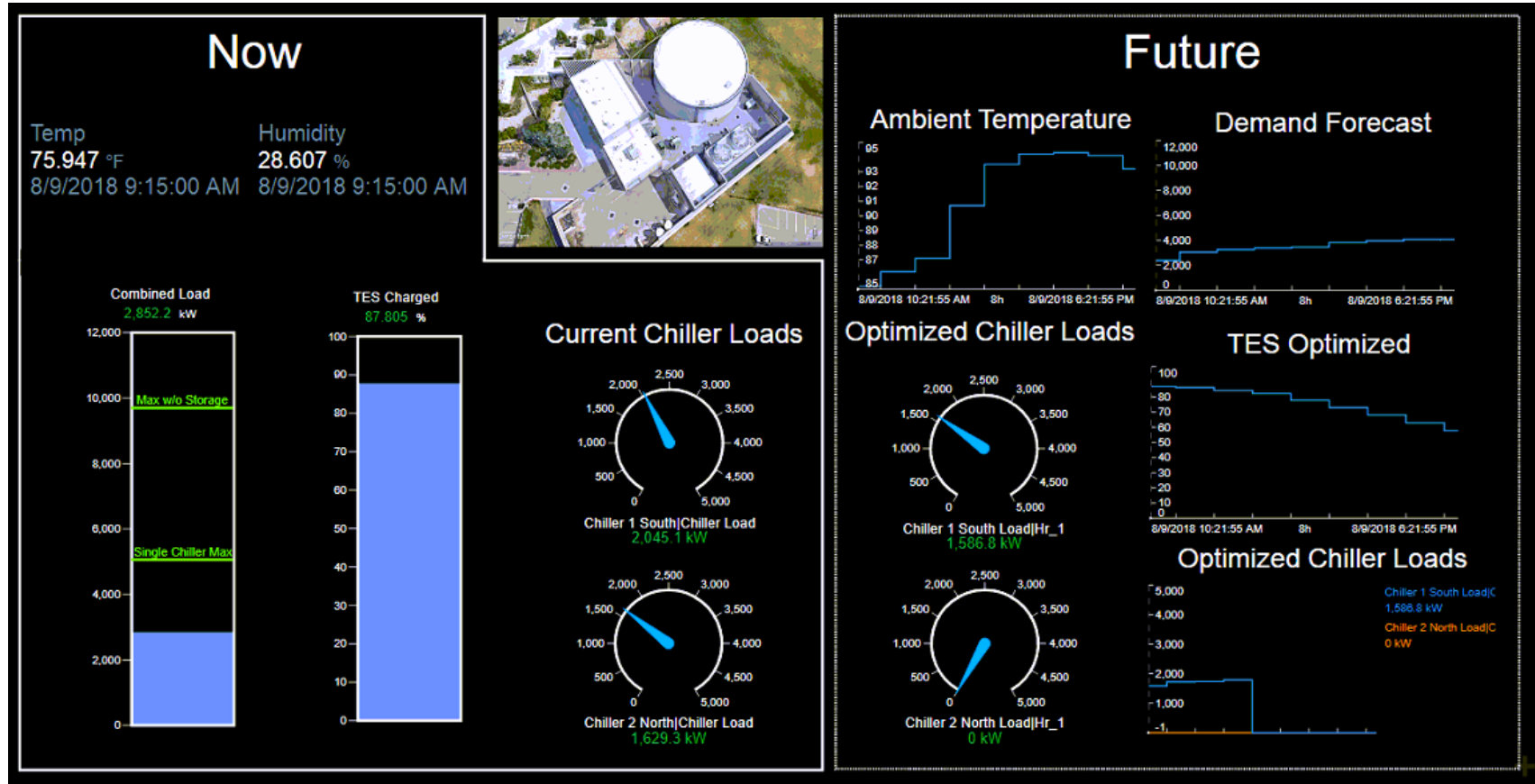
*The 12-h time window manual control was unable to achieve the starting energy storage

[†]The 24-h and 72-h BnB failed to converge after over 24 h of computation

Building an Optimization Application around PI



PI Vision Dashboard



Future Work

- More verification and validation
- Human-in-the-loop operation
 - Advisory mode using PI Vision
- Close the loop
- Stochastic + dynamic optimization
 - Account for model uncertainty using probabilistic methods

Next Steps:

- Nexus of ML and BI Analytics
 - Operationalize ML
- Educating next gen
 - Data infrastructure, analytics, computational intelligence, ...

Acknowledgements

- OSISoft and John Matranga
- Utah office of Science Technology and Research (USTAR)
- Aaron Young, Landen Blackburn, Titus Quah
- University of Utah Facilities Management Group



Appendix Slides

Modeling the Chillers

First Principles Model of a Chiller by Gordon, Ng, and Chua:

$$P = \frac{Q}{\text{COP}} = -Q + \left(\frac{T_c^{\text{in}}}{T_e^{\text{out}}} \right) Q + \left(\frac{q_e T_c^{\text{in}}}{T_e^{\text{out}}} - q_c \right) + \left(\frac{q_e}{M_c T_e^{\text{out}}} \right) \left(\frac{q_e T_c^{\text{in}}}{T_e^{\text{out}}} - q_c \right) + \left(\frac{Q^2}{T_e^{\text{out}}} \right) \left(\frac{T_c^{\text{in}}}{T_e^{\text{out}}} \right) \left(\frac{1}{M_c} + \frac{1}{M_e} \right) + Q \frac{\frac{q_c}{M_e} + \frac{q_e T_c^{\text{in}}}{T_e^{\text{out}} M_c} + \left(\frac{T_c^{\text{in}} q_e}{T_e^{\text{out}}} - q_c \right) \left(\frac{1}{M_c} + \frac{1}{M_e} \right)}{T_e^{\text{out}}}$$

Gordon, J. M., Ng, K. C., & Chua, H. T. (1995). Centrifugal chillers: thermodynamic modelling and a diagnostic case study. *International Journal of refrigeration*, 18(4), 253-257.

Modeling the Chillers

First Principles Model of a Chiller by Gordon, Ng, and Chua:

$$P = \frac{Q}{\text{COP}} = \frac{Q}{\left(\frac{q_c}{M_e} + \frac{q_e T_c^{\text{in}}}{T_e^{\text{out}} M_c} + \frac{\left(\frac{T_c^{\text{in}} q_e}{T_e^{\text{out}}} - q_c \right) \left(\frac{1}{M_c} + \frac{1}{M_e} \right)}{T_e^{\text{out}}} \right)}$$

Gordon, J. M., Ng, K. C., & Chua, H. T. (1995). Centrifugal chillers: thermodynamic modelling and a diagnostic case study. International Journal of refrigeration, 18(4), 253-257.

Optimization Problem Formulation

- Objective: Minimize total cost

$$\min_{u_i} F = \sum_i \left[C_f (W_{f,GT,i} + W_{f,HRSG,i} + W_{f,BR,i}) - C_{e,i} P_{net,i} \right] (\Delta t)$$

- Decision variables

$$u_i = \left[Q_{3.1} \cdots Q_{6.3} \delta_{3.1} \cdots \delta_{6.3} Q_{TIC} \theta_{IGV} W_{f,GT} W_{f,HRSG} W_{f,BR} W_{s,EXT} P_{net} \right]^T$$

- Load constraints

$$P_{GT,i} + P_{ST,i} - P_{net,i} \geq L_{E,campus,i} + \sum P_{ch,i} + \sum P_{aux,i}$$

$$\sum_j Q_{i,j} - Q_{TES,i} \geq L_{C,i} + Q_{TIC,i}$$

$$W_{S,EXT,i} \geq L_{H,i}$$

Assumptions

- One-hour time intervals
- Steady-state models for all generation equipment
 - Max settling time ~ 15 minutes
- 24-hour time horizon
 - Storage capacity ~ 2-6 hours full load
- Discrete dynamics for storage

$$E_{TES,i} = E_{TES,i-1} + (Q_{TES,i} - E_{loss,i}) \Delta t$$

$$Q_{TES,i} = \sum_j Q_{i,j} - (L_{C,i} + Q_{TIC,i})$$

Dynamic Optimization Problem Summary

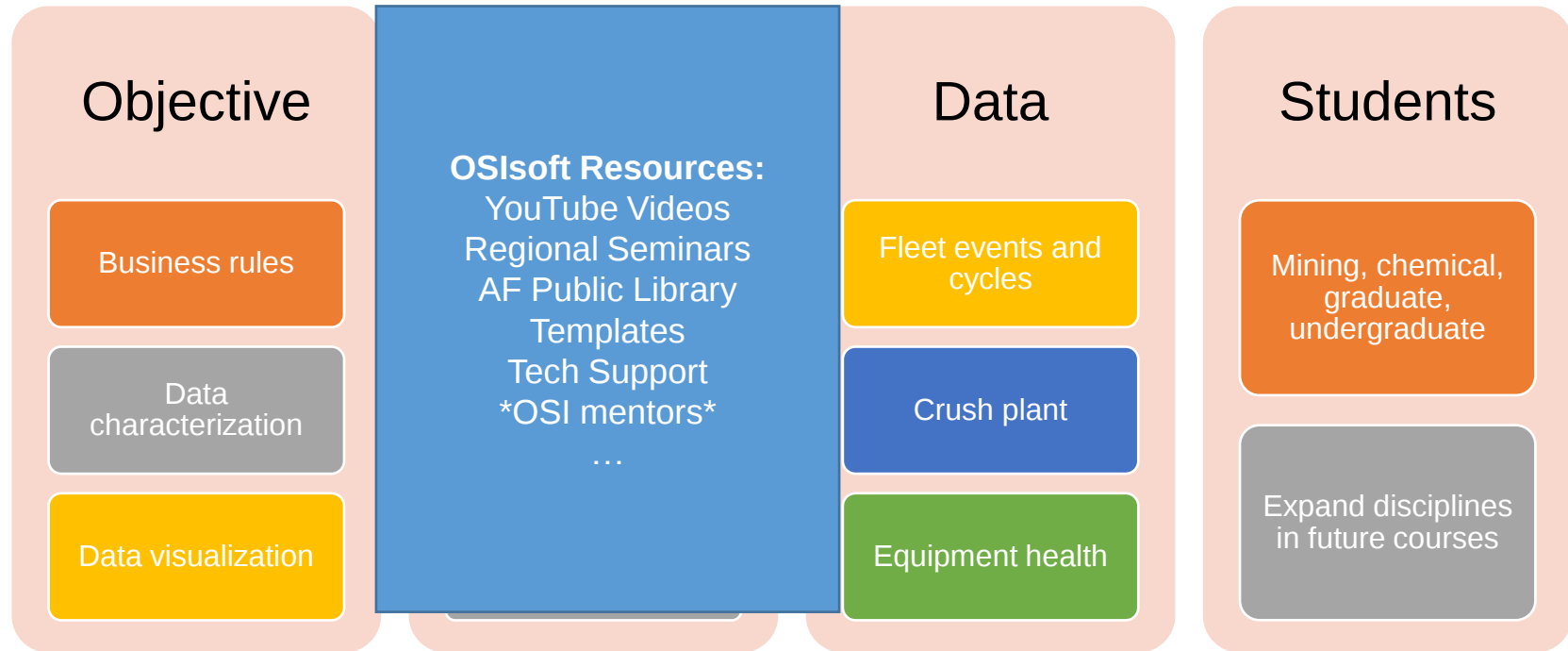
- Mixed-integer Nonlinear Program (MINLP)
- 600 decision variables
- 216 binary constraints

$$\delta_j \in [0,1]$$

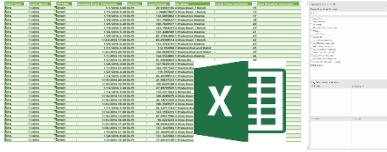
$$\delta_j Q_{j,\text{lo}} \leq Q_j \leq \delta_j Q_{j,\text{hi}}$$

- Original Approach: Full MINLP solved using BONMIN solver
 - 27-hour solve time (2.5 GHz processor)
 - Curse of dimensionality
 - Equipment chatter

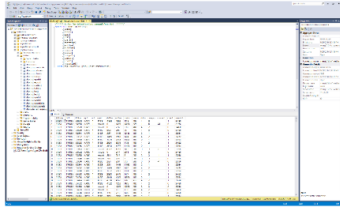
Data Management Spring 2019



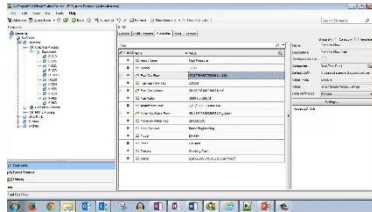
Connecting engineering and operational standards to business rules



Excel tables & pivot



SQL tables & views



PI AF / Event Frames

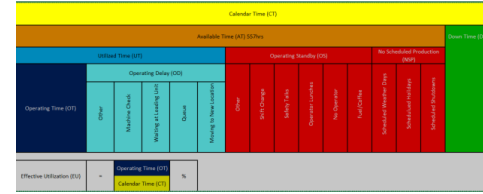
Business rules to
engineering standards



Business rules to
engineering standards



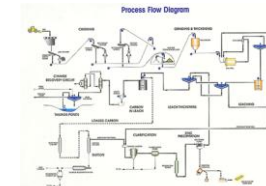
Business rules to
engineering & operational
standards



Time Usage Model

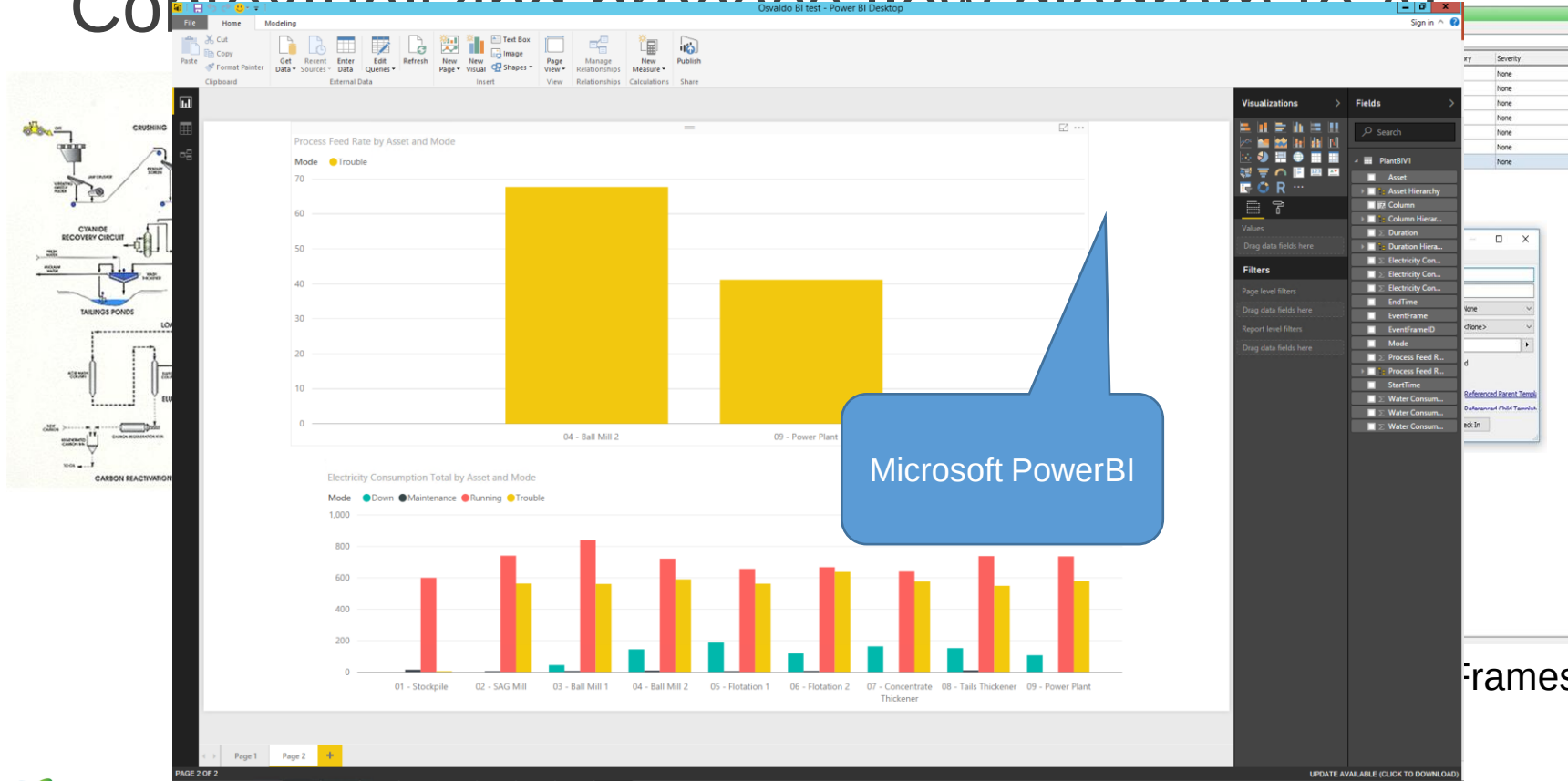
Item	Description
Item	Item is identified by item name. Items can be grouped into categories. Item name is a key for identifying item.
Material	Material is identified by material name. Material can be grouped into categories. Material name is a key for identifying material.
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Material Hierarchy



Process Flow Diagram

Contextualizing process flow diagram to AIF



frames

Initial lessons learned

- Introduce concepts gradually
 - I do, we do, you do approach
- Infrastructure always a challenge
- Business rules first, visualization second
 - Visualizations important business rules foundational
- Students are enjoying it!