UPISC UNIVERSITY OF PITTSBURGH INFRASTRUCTURE SENSING

COLLABORATION WORKSHOP

NATIONAL ENERGY TECHNOLOGY LABORATORY

Digital Twin Models and Interfacing with Real-Time Sensing

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Lea Boche is a Technical Leader at the Electric Power Research Institute (EPRI). She is responsible for data analytics and machine learning applications in the Enabling Technologies R&D group in EPRI's Generation Sector.

Boche began her work at EPRI in its Heat Rate Improvement R&D program, focused on power plant simulations and project management. Following this she worked in the cross-sector initiative AI.EPRI to help further the use of Artificial Intelligence in the industry.

Boche's previous experience includes project engineer and, later, R&D project management for STEAG Energy Services GmbH, Department System Technologies - Energy Management Systems, where she led development of a decision-support software and was the lead for the innovation management of System Technologies department. She was a lecturer on power plant design studies and simulations at Fachhochschule Dusseldorf and a research associate at TU Berlin, Institute for Energy Technologies.

She has a bachelor's degree in mechanical engineering from RWTH Aachen; a master's degree in energy and process engineering from Technical University Berlin, and a PhD in Energy Engineering from Technical University Berlin.

Digital Twin Models and Interfacing with Real-Time Sensing

EPRI

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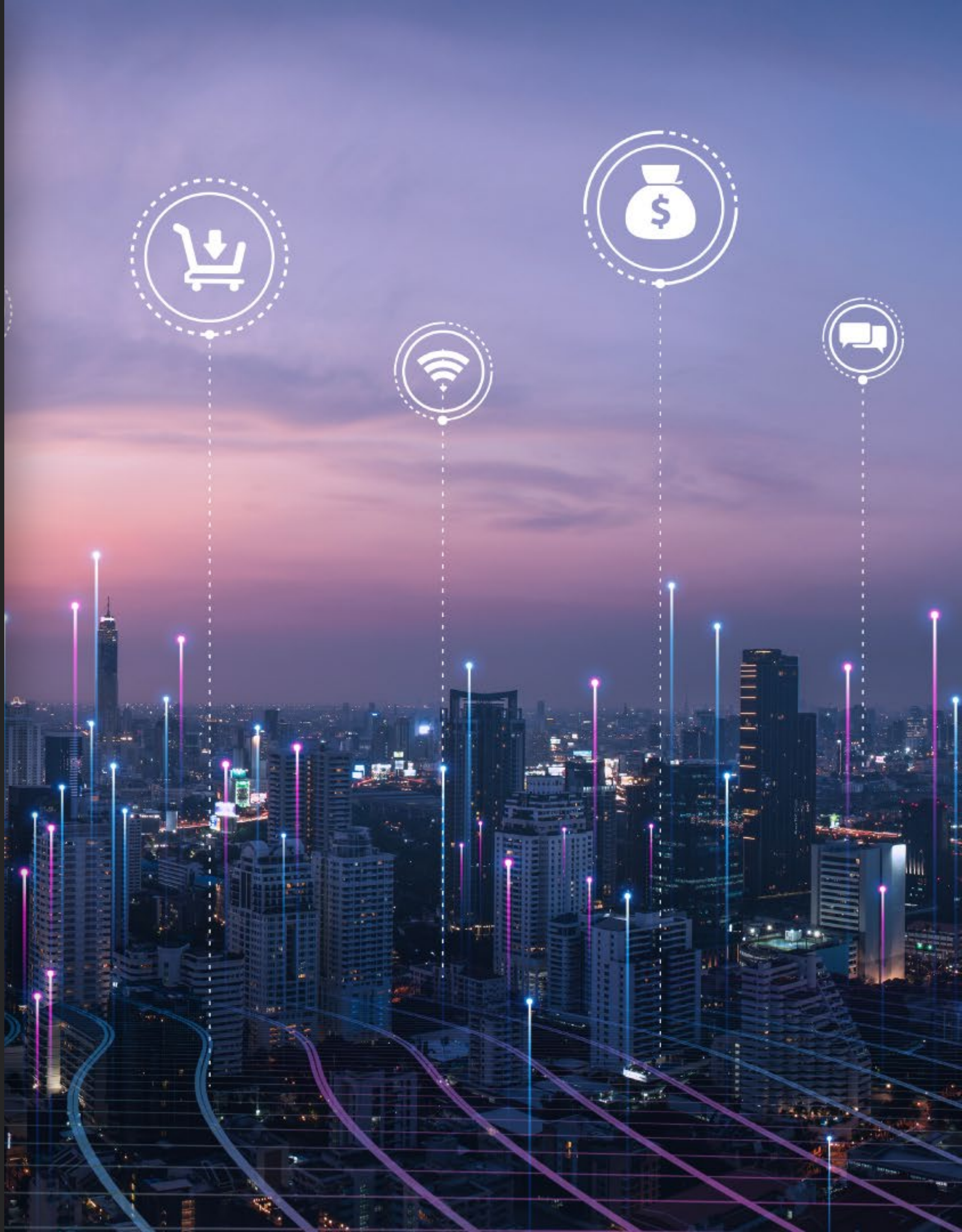
EPRI

Pittsburgh, 8/25/22



Outline

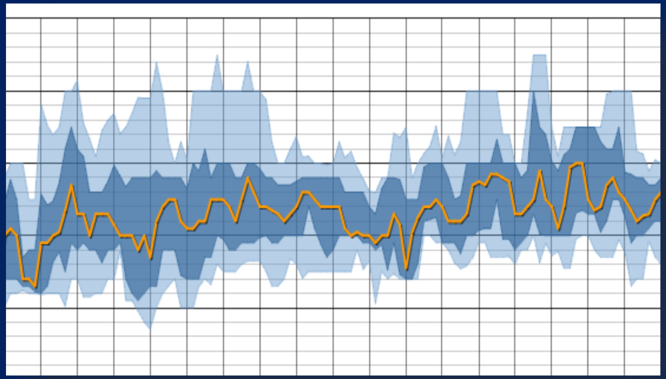
- Discuss AI/ML techniques (bias towards how they are used for DT)
  - Regression (ANN)
  - Calibration
  - Classification
  - Joining a problem to resolve technique
- Digital Twin
  - What is a digital twin – components and challenges?
  - Physical models
    - Requirements
    - Set up
    - Gas Turbine Models
  - How it all gets combined
    - Model creation
    - Model Calibration
    - Model Deployment

Information through Analysis: Spectrum of Data Analytics

Operational

Computer-Assisted SME

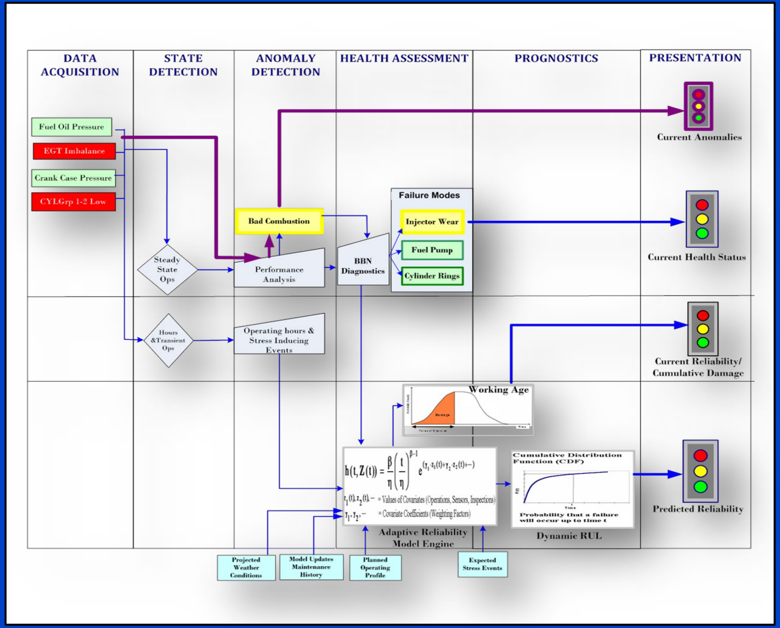
- PI
- Advanced Pattern Recognition (APR)
- Model Development
- Alarm Limits



Predictive

SME-Validated

- Advanced Infrastructure
- Edge Analytics
- Prognostics / RUL



Prescriptive

Computer-Guided SME

- Integrated Technical / Environment / Business Data
- Embedded Complexity

Gas Turbine: Typical Monitoring & Challenges

Instrumentation Problems

Tuning/Performance Deviations

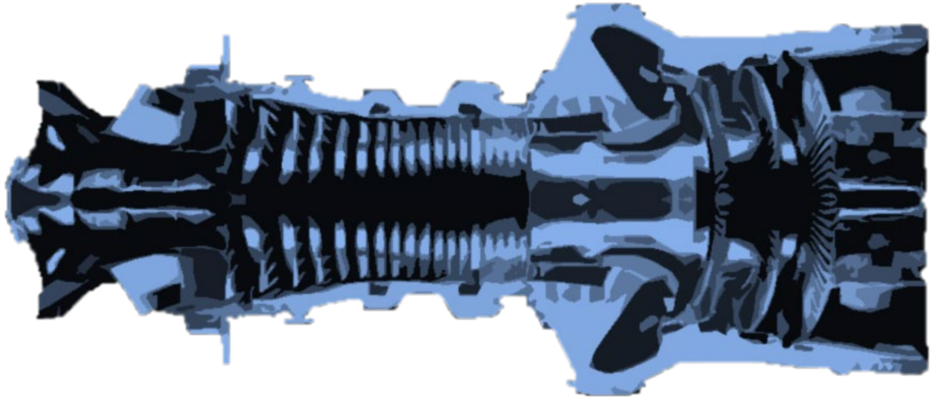
Hardware Issue Development

Current Advanced Pattern Recognition

Great Indicator of Differences

Lacks Causation Indication

90%+ of Alarms Results in Model Retraining

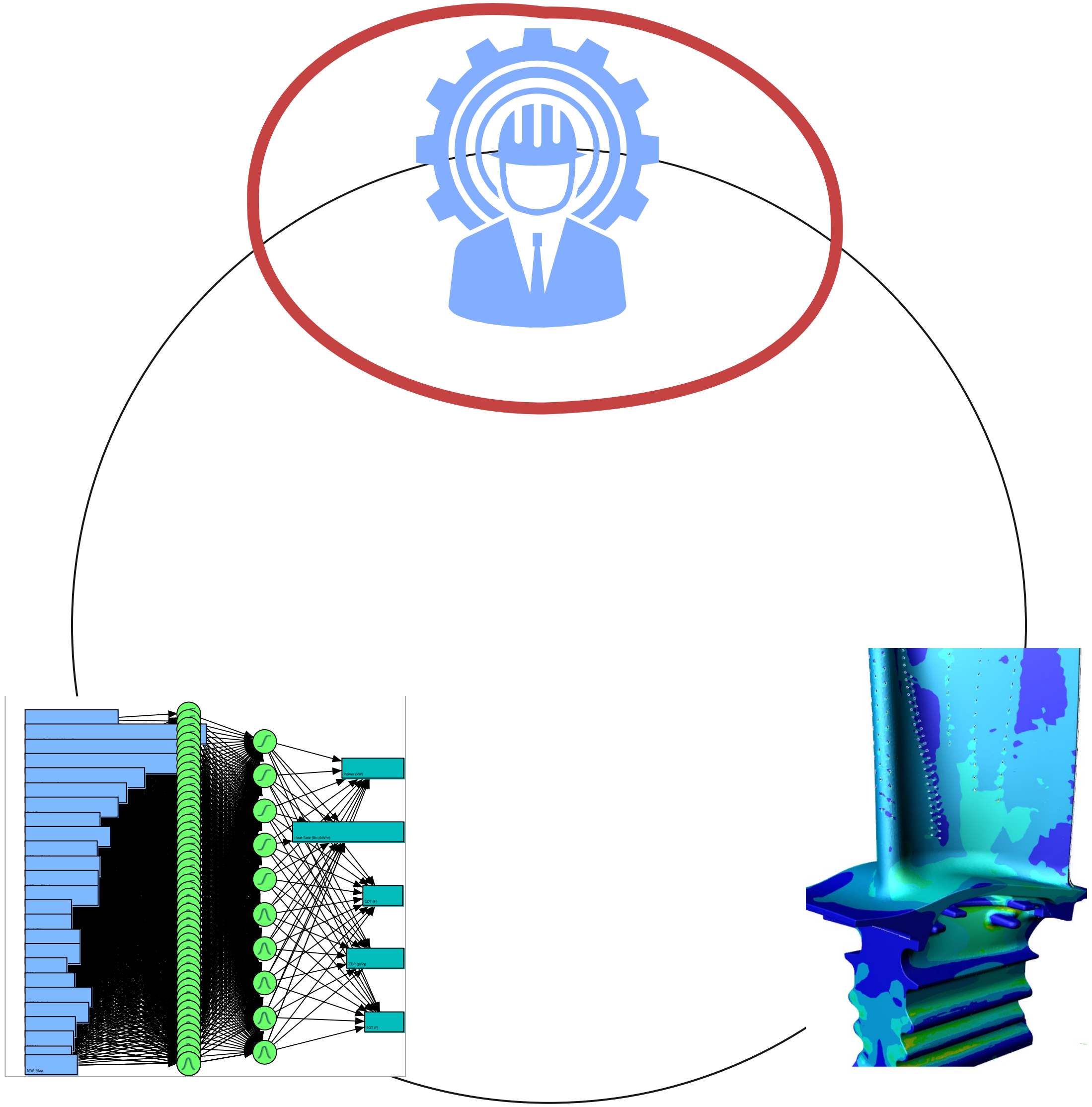


Machine Learning & 1st Principle Physics

Increased Sensitivities to Real/Actionable Issues

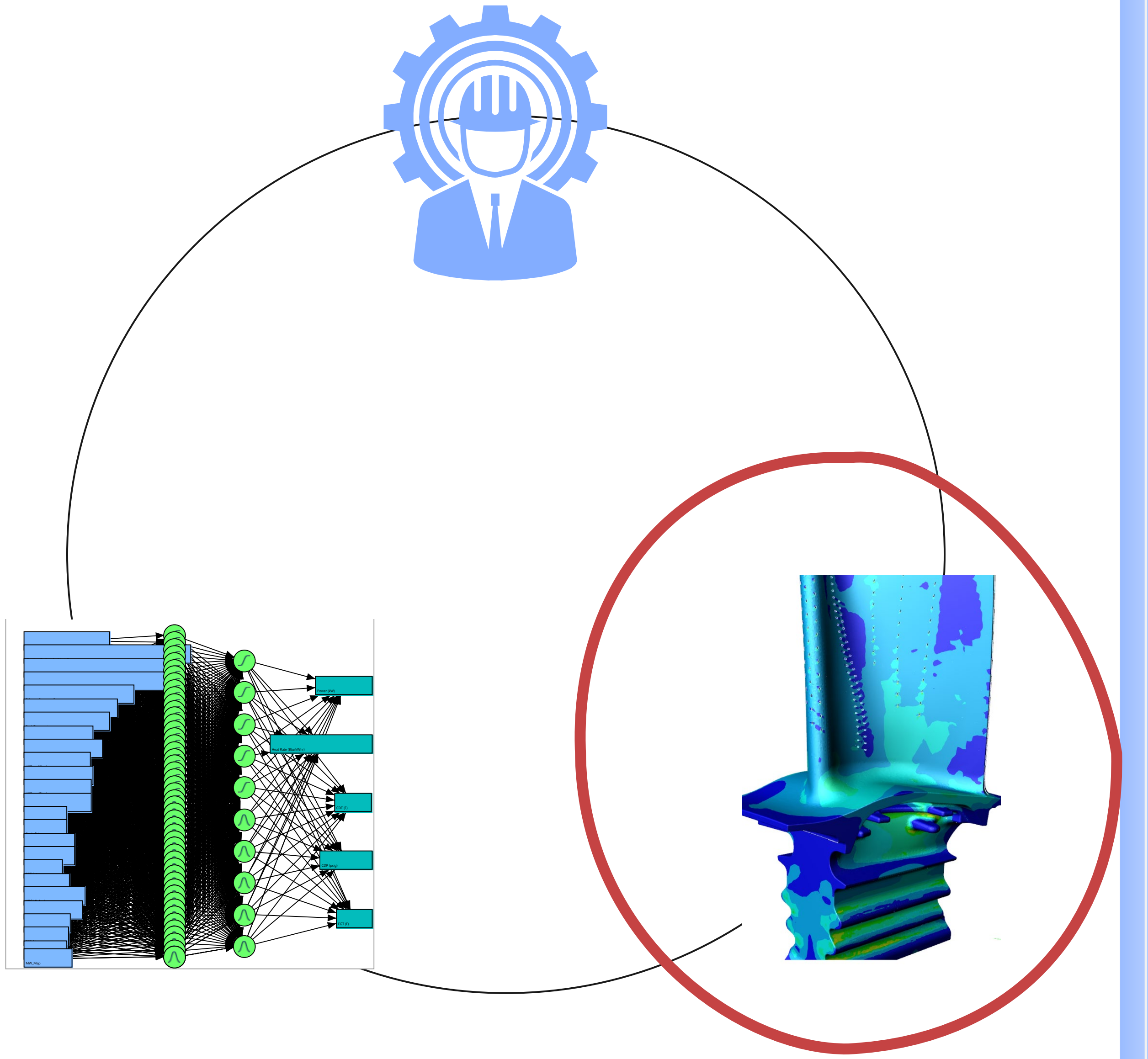
Allows for Computer Aided Diagnostics/Prognostics

Requires Data and SME Knowledge



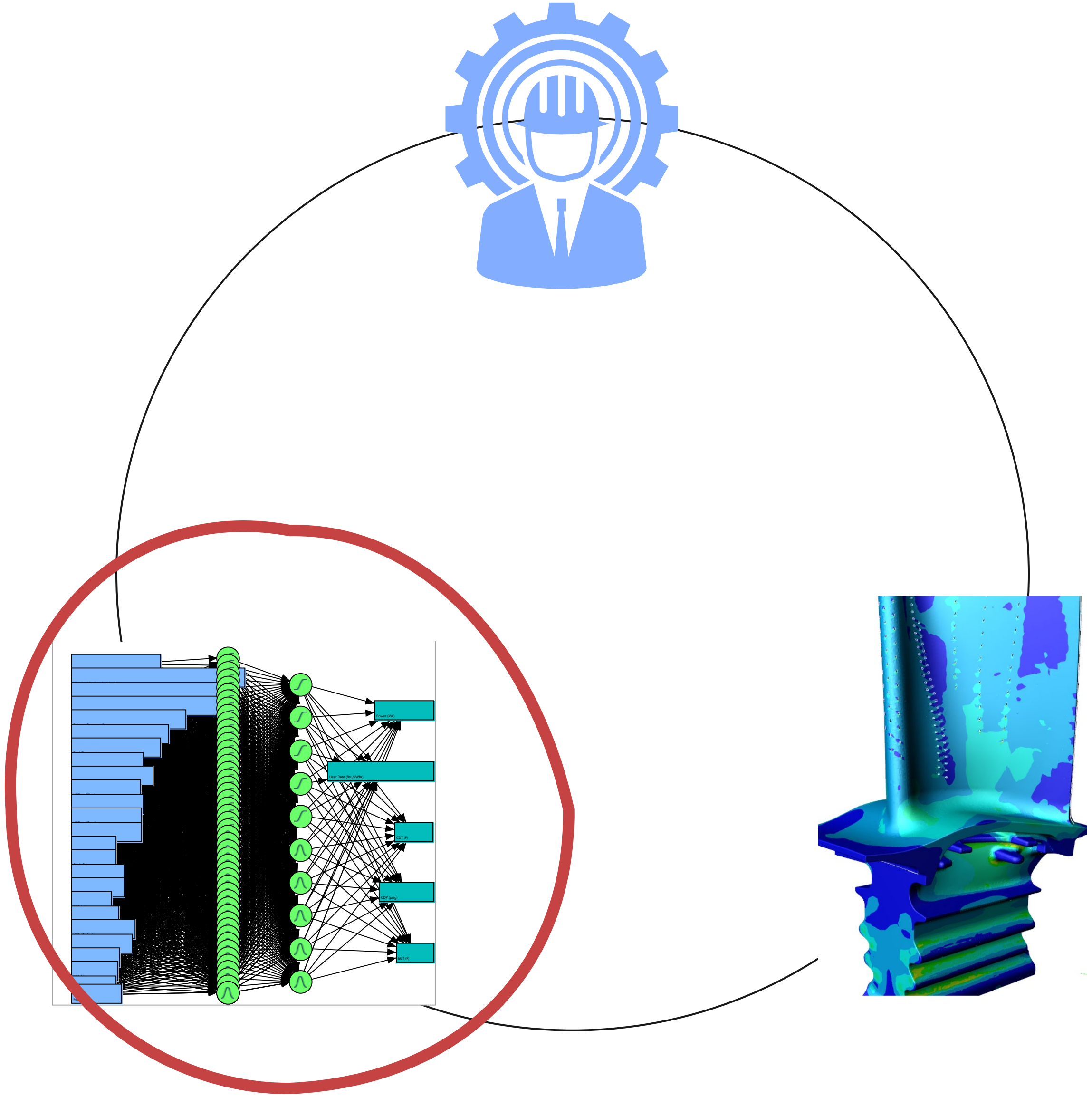
SUBJECT MATTER EXPERTISE

- Provides context
  - What data is required?
  - What does the data mean?
  - How should I interpret data?
  - What models are appropriate?
  - How to handle **real-world** systems
  - Establish trust with model
  - Help define use cases



PHYSICAL MODELING

- Provides ground truth to data
  - Underpins data-driven approaches
  - Independently trusted tool
  - Enables parametric study ('what-if') **–Cannot do with data alone**
  - Enables intelligent extrapolation **–Cannot do with data alone**



ARTIFICIAL INTELLIGENCE / MACHINE LEARNING

- AI Brings it all together!
  - Calibration
  - Acceleration of execution
  - Portable
  - Trend identification
  - Can learn complex relationships
- Dangerous in untrained hands
  - Very easy to create a model that ‘looks good’
  - Often provides erroneous results

AI/ML Techniques and Categories

AI/ML Techniques – Continuous Data

<u>You want to be here</u>

<u>Most of us are here</u>

Supervised

- Dataset has known inputs and outputs – **up to engineer to determine causation**
- Dataset can be categorized <u>(labeled)</u> a priori
- Most engineering problems fall into this category
- Includes
  - *Classification* – **is this a specific fault?**
  - *Regression* **– 'Curve fit'**

Unsupervised

- Inputs and outputs are abstract or cannot be defined
- Appropriate when relationship between variables is unknown (i.e., social behavior)
- Includes
  - Clustering – **is this different (e.g., APR)**

What are the Challenges with Supervised Learning?

Common Challenges

- No process to establish **'what is a good initial model?'**
- No process to update and improve model accuracy over time

Unsupervised learning (APR)

- **Requires little problem setup to get running**
- Running != useful analysis
- High false alarm rate because you cannot control 'separation' between good and bad

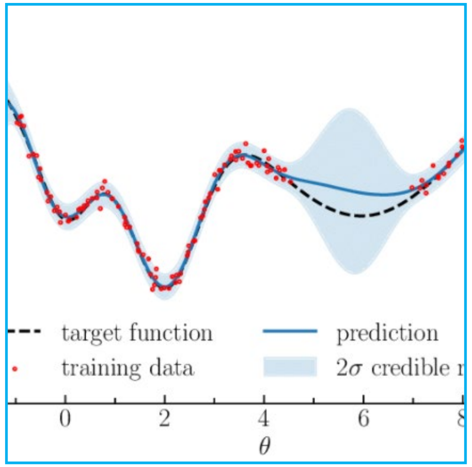
Supervised learning requires additional preparation

- **Data quality impacts model quality – model must be robust!**
- For classification problems – must label data or develop classification rule
- Often requires additional physics informed modeling to make sense of time-series data

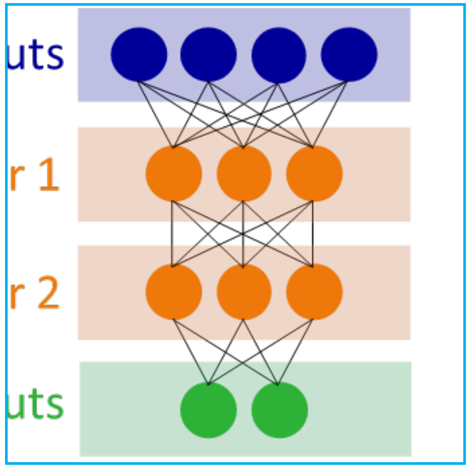
Classification vs. Regression

Regression – Predict a value(s)

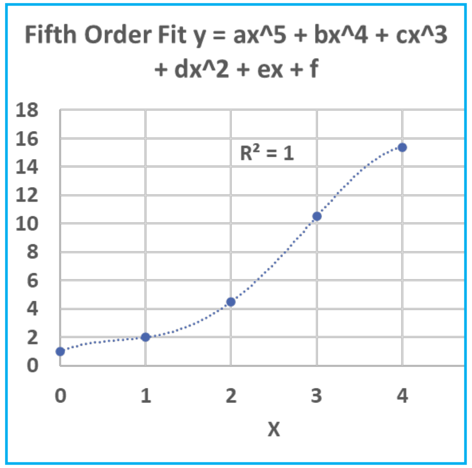
Gaussian Process



Neural Networks

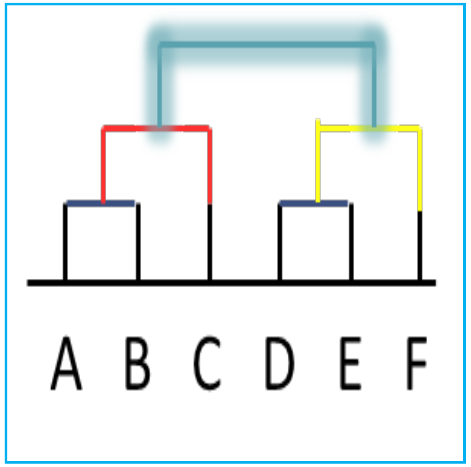


Multivariate Poly.

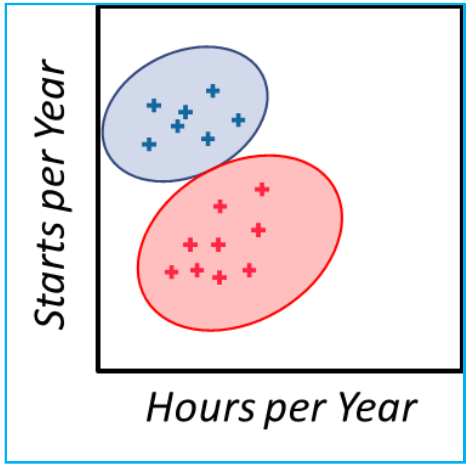


Classification – Where does this 'thing' belong?

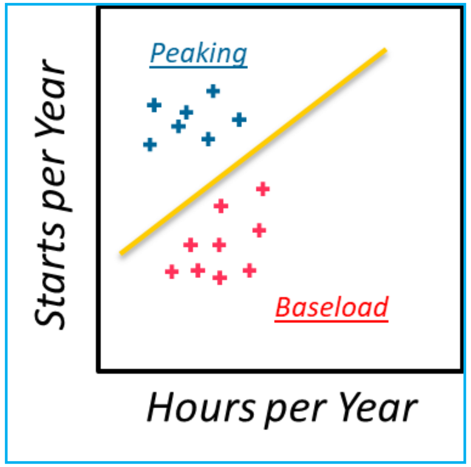
Hierarchical



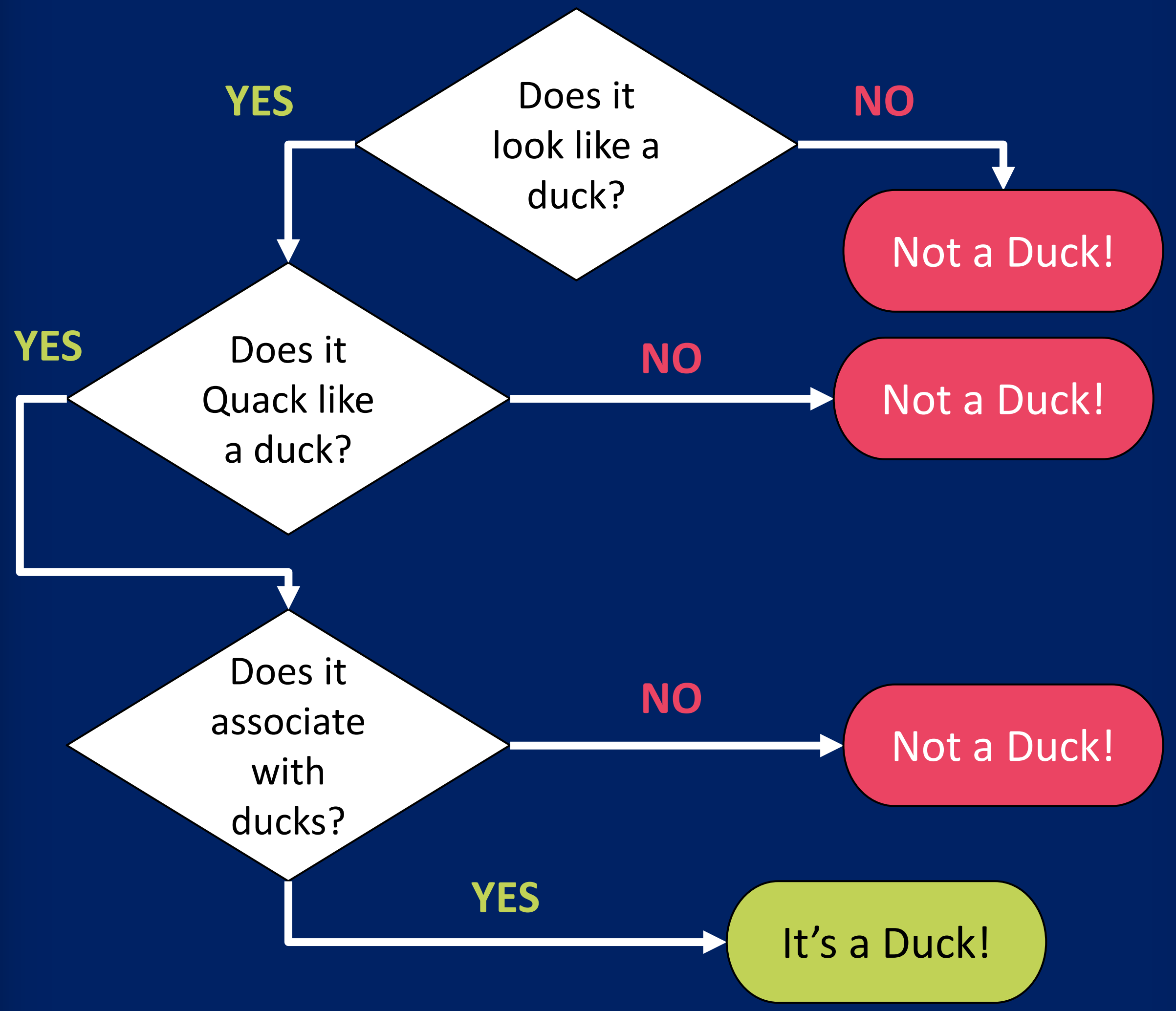
Unsupervised



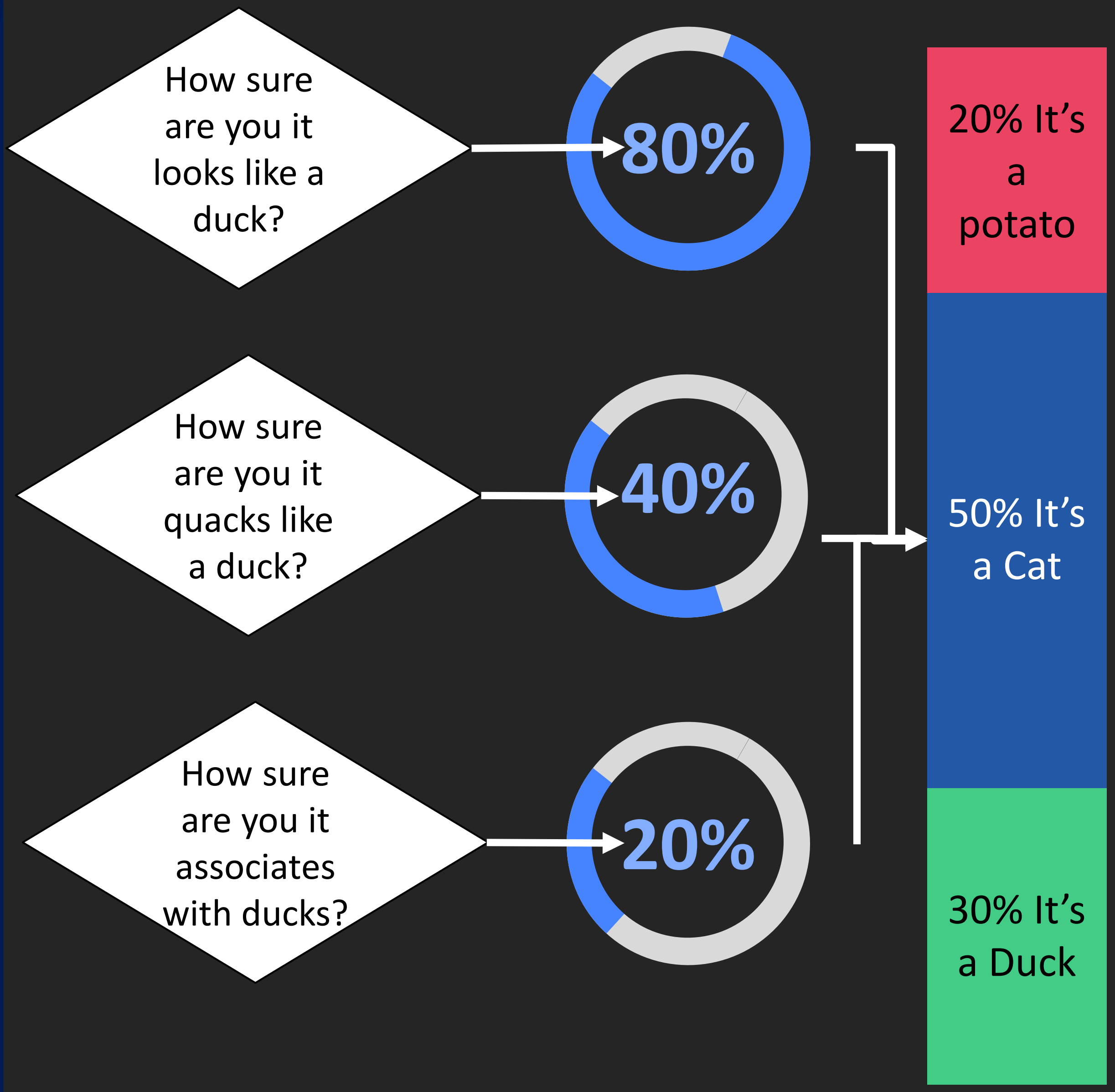
Supervised



WHO TOOK LOGIC IN COLLEGE?



DETERMINISTIC MODELS



PROBABILISTIC MODELS

One Last Comparison…Probabilistic vs. Deterministic

Deterministic

- Takes data used for fitting at face value
- Prediction is a single value
  - MW = 186.5
  - The compressor is **faulted**
- **Easiest to use and comprehend**
- Less robust to lack of knowledge
  - Insufficient problem definition
  - Noisy or incorrect data

Probabilistic

- **Considers uncertainty in fitting data or prediction**
- Prediction is a bounded estimate
  - MW = 181 to 193 MW with 90% confidence
  - The compressor is faulted with 77% certainty
- Many end users struggle since there is not a single value predicted; **however**
  - Very useful for trending noisy data

A Few Source of Uncertainty

Measurement Uncertainty

- Intrinsic inaccuracy in sensor
- Drift or noise in measurement
- Error in the recording chain (e.g., charge amp, DAQ, etc.)
- Dropouts (e.g., wireless sensor)
- Sensor placement
- Number of sensors (e.g., exhaust thermocouples)

Data Storage Uncertainty

- Dropouts from SCADA to Historian
- Data compressions settings (inconsistent settings also cause issues)

Model Uncertainty

- Appropriateness of underlying physics
- Assumptions you consciously made
- **Assumptions you didn't even know you made (BIG ONE)**
- Calibration technique
- Model definition
- Garbage in – garbage out

Characteristics to Consider

- Do I have specific responses (outputs)?
- Are my responses:
  - Continuous? [1.4, 6.7, 10.4]
  - Discrete Numerical? [1,2,3,4]
  - Categorical?
  - Mixed?

- Is the training data synthetic or measured?
  - How much noise in your dataset?
  - Can you denoise the data through signal analysis?
  - Reconcile with a model?
- How noisy is your dataset?

What is Digital Twin?

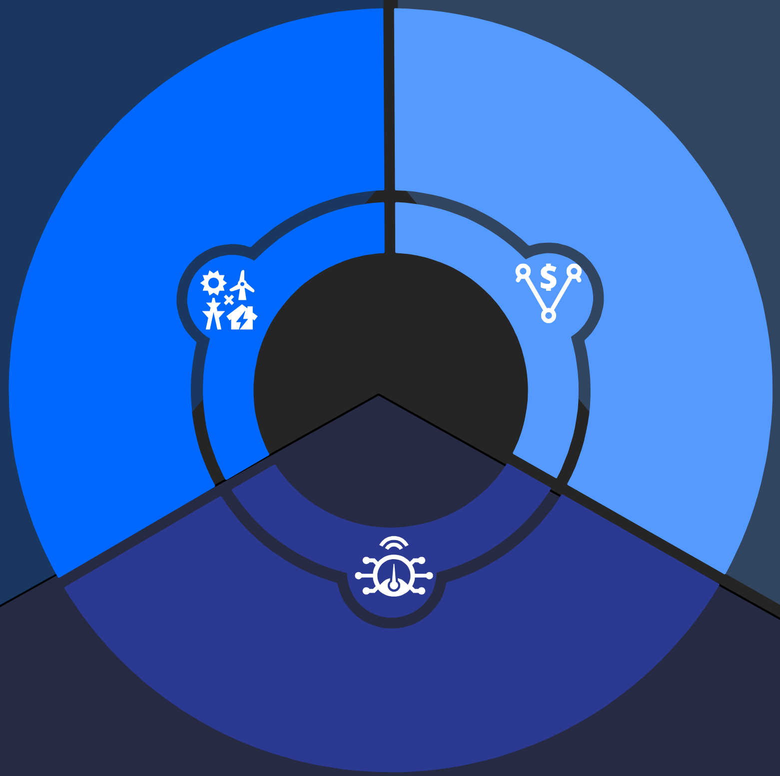
Digital Twin Applications

Prognostics

- Identifies changes in component performance pre/post outage for assessment of outage success
- Assist in root cause analysis of failures
- Provides component specific degradation information
- Generates fault signatures for APR software
- Reduces uncertainty in APR fault signature identification through addition of virtual sensors

"What-if" Scenarios

- Provide physics-based prediction of plant performance change due to upgrades (i.e., compressor upgrades, filter changes, HRSG upgrades, control curve changes, other hardware changes)
- Predict impact HRSG and BOP upgrades and controls changes
- Transient Response Optimization for Renewables Integration



Diagnostics

- Informs condition-based maintenance
- Informs power production planning through accurate short- and long-term future performance prediction
- Couple with APR future prediction trending to predict degradation rates of specific components to inform maintenance planning

Key Characteristics

Connectivity

- Can integrate into any M&D setup through AI encapsulated regression model
- Can run in real time using Historian data

Physics-based

- Individual models created using trusted Physics-based commercial software (NPSS)
- Variable fidelity – can adapt model to varying plant data quality or instrumentation availability

Digital Twin

Adjustable

- Can calibrate to any gas turbine for which a physics-based reference model has been created
- Equations created for integrated monitoring are self-calibrating as new data comes in from Historian

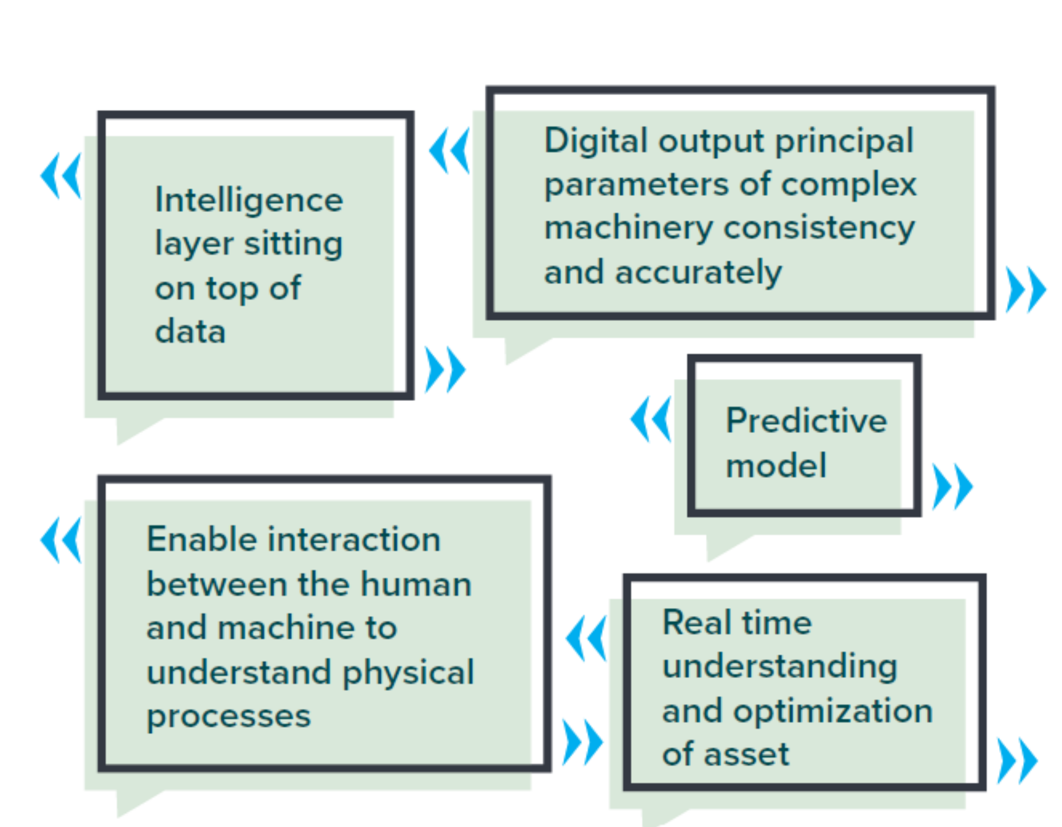
Modularity

- Can adapt to varying instrumentation loadout
- Can be used to predict virtual sensors (e.g., shaft power in mechanical drive application *or* fuel flow in case of poor measurements)

The Making of a Digital Twin

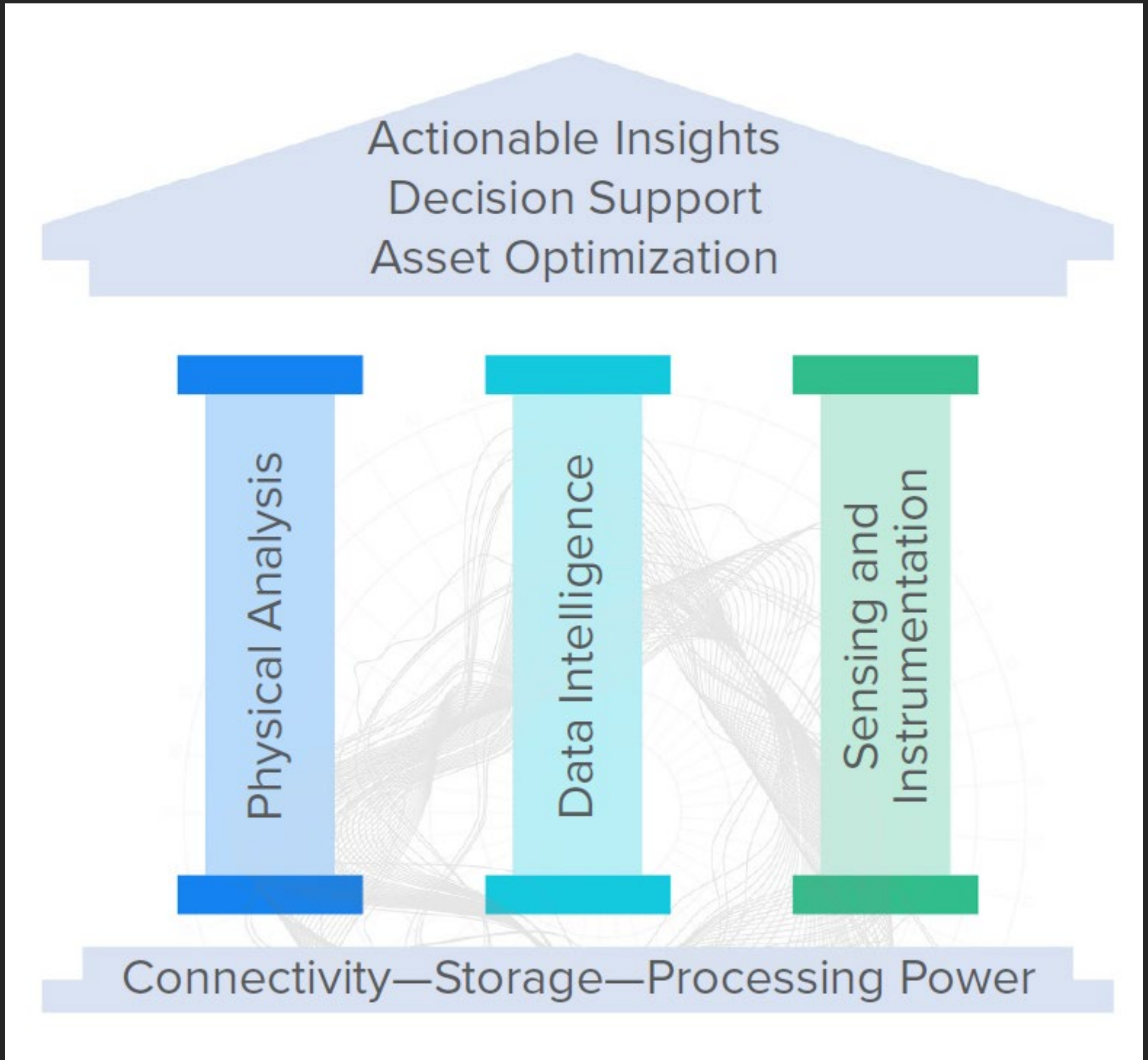
- A DT purposefully integrates trusted tools and techniques to give better insights into assets to improve decision-making
- We asked several EPRI members what DT meant to them
- While varied, a theme emerging:
  - A DT integrates data, models, and human input to provide improved insight

Real Quotes from Real Engineers



The Road to Digital Twins

- Like a building a house, foundation of DT
  - Connectivity, Storage, and Processing Power
- In order to use a DT to create actionable insights and support decision making, several key pillars are needed
  - Physics-based Models
    - Allows for advanced computer modeling of the underlying process or system
  - Data-driven Intelligence
    - Includes ML, AI, data-driven modeling and insights (i.e., APR)
  - Sensing and Instrumentation
    - Improved sensing technologies at lower cost enable more information to be obtained about the state of an asset which can be used to improve physics and data models



The Road to Digital Twins

- Once built, a DT provides improved decision making in a multitude of ways.
  1. The integration with physics-based modes provides additional insight into the current health and capabilities of an asset
  2. The improved knowledge supports more informed decision making and optimization on asset operation and maintenance decisions

Digital Twins leverage recent advances in computational, storage, and connectivity to provide integrated decision making based on trusted tools and techniques.

Connecting Asset, Data Processing, and Human Interaction

Identify Easy Wins

- Connected Instrumentation
- Data storage connected to centralized data warehouse
- Appropriate Instrumentation

Data Processing and Analytics

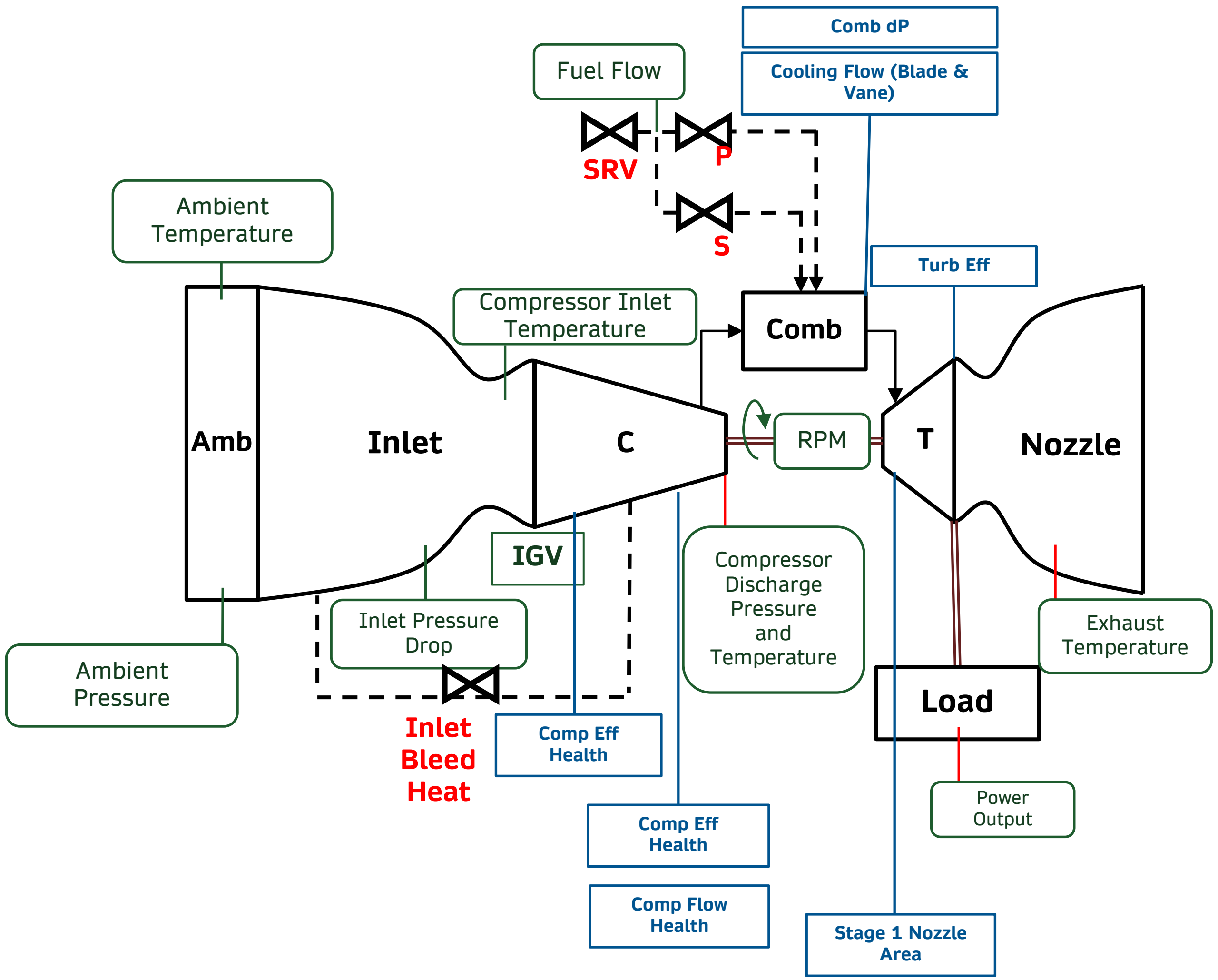
- Physics-Based Models
- Artificial Intelligence and Machine Learning
- Learning Models
- Predictive Capability

Insights and Interactions

- Design Changes
- Quality Control
- Operations (Performance, Reliability)
- Maintenance Services

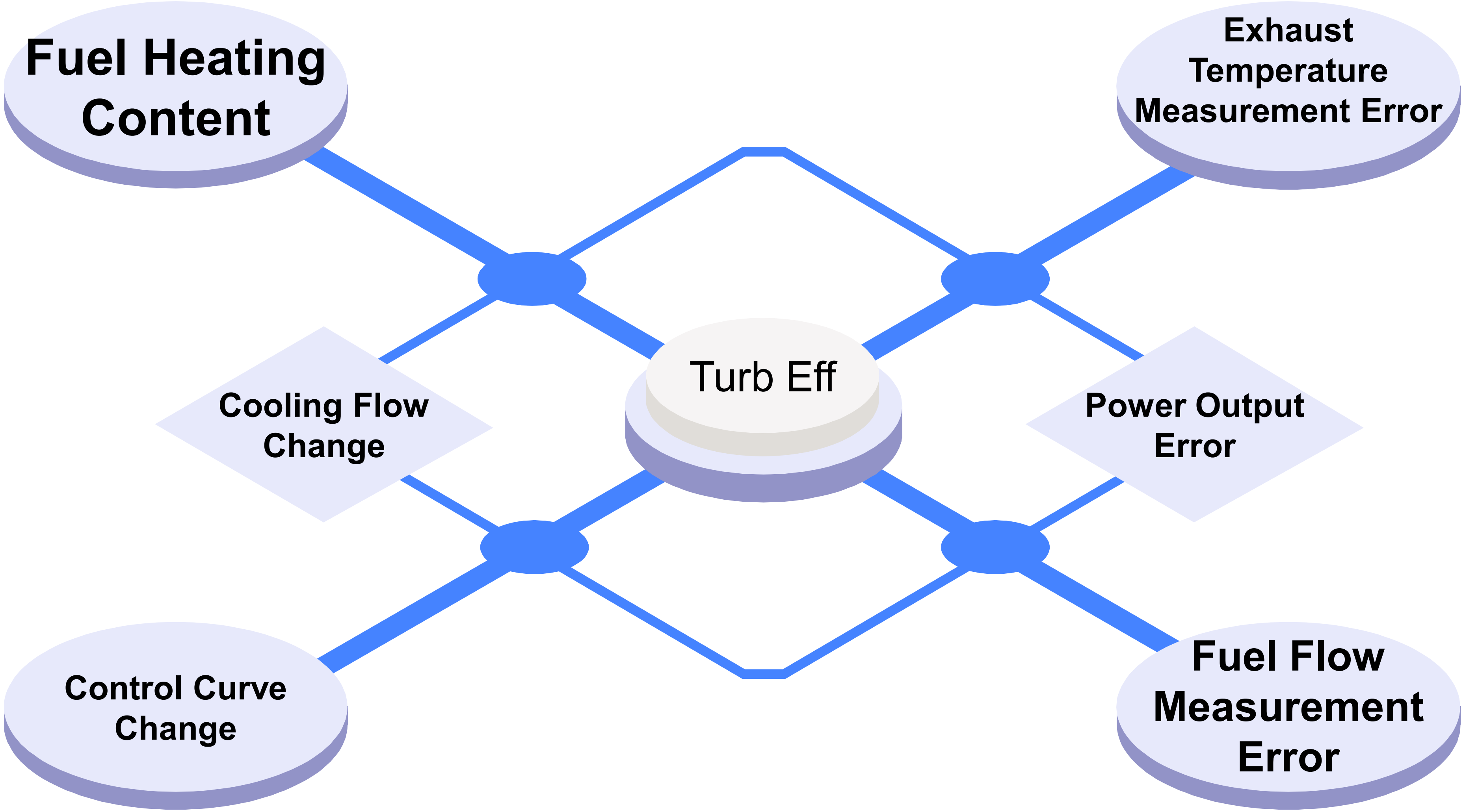
Physical Model Requirements

Hybrid Intelligence



- Traditional Sensors
- Virtual Sensors

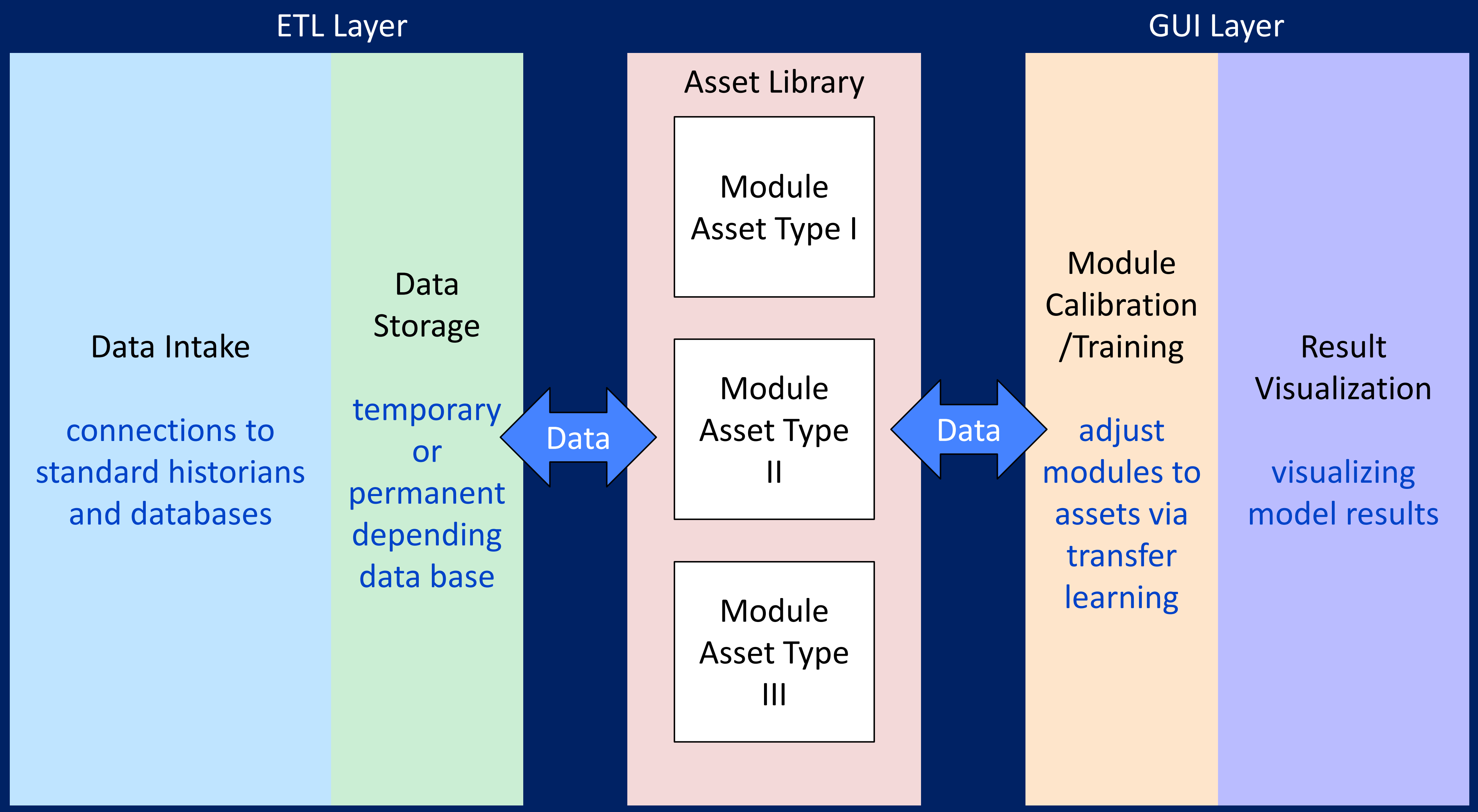
What Contributed to Turbine Efficiency?



Digital Twin Can Help "De-Convolute" Compounded Influences

Digital Twin Model Calibration Setup and Deployment

Proposed Digital Twin Framework

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Virtual Sensor List and Descriptions

Virtual Sensor	Description / Usage
Comp Eff. Health	Unbiased estimate of compressor efficiency. Provides a shift relative to ideal conditions such that the signal is invariant to operating conditions or load.
Comp. PR Health	Unbiased estimate of compressor pressure ratio. Provides a scale factor relative to ideal conditions such that the signal is invariant to operating conditions or load.
Comp. Flow Health	Unbiased estimate of compressor mass flow capability. Provides a scale factor relative to ideal conditions such that the signal is invariant to operating conditions or load.
Stage 1 Nozzle Area	Turbine nozzle choke area
Turbine Eff	Unbiased estimate of turbine efficiency. Provides a shift relative to ideal conditions such that the signal is invariant to operating conditions or load.
Cooling Flow	Unbiased estimate of chargeable and nonchargeable cooling flow from the compressor to the turbine. Provides a scale factor relative to ideal conditions such that the signal is invariant to operating conditions or load.
Comb. dP	Unbiased estimate of combustor pressure drop. Provides a scale factor relative to ideal conditions such that the signal is invariant to operating conditions or load.
Ambient Pressure Bias	Estimated error in ambient pressure measurement
CDP Bias	Estimated error in CDP measurement
EGT Bias	Estimated error in EGT measurement
IGV Bias	Estimated error in IGV measurement

Case Studies

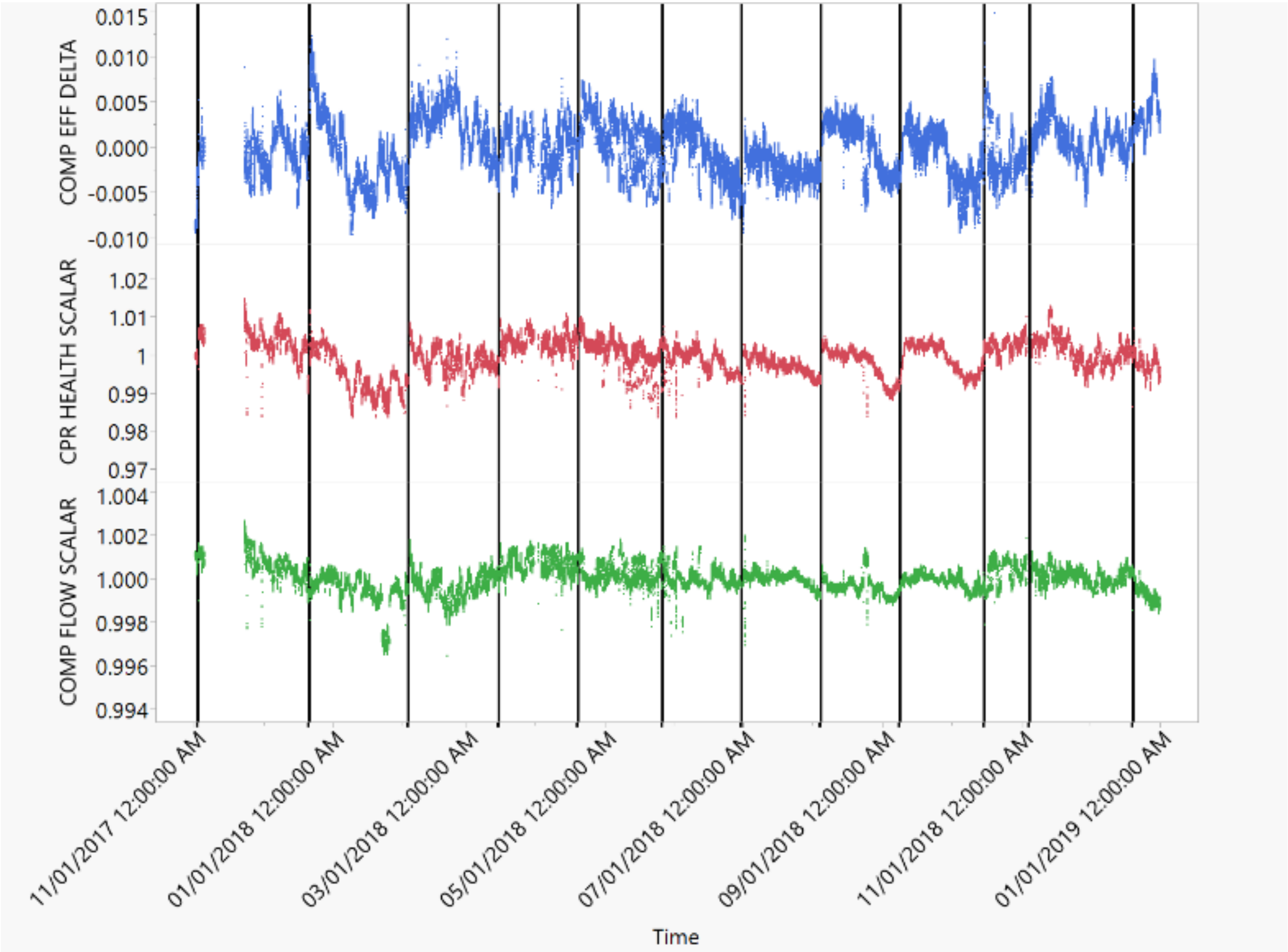
- Power Loss Due to Compressor Degradation
- Compressor Liquid Fouling Event
- Post Major-Outage MW Reduction
- Majority taken from:

  The EPRI Gas Turbine Digital Twin – a Platform for Operator Focused Integrated Diagnostics and Performance Forecasting *Proc. ASME. GT2021, Volume 4: Controls, Diagnostics, and Instrumentation; Cycle Innovations; Cycle Innovations: Energy Storage; Education; Electric Power, V004T09A009, June 7–11, 2021*

  - **Paper No:** GT2021-59572

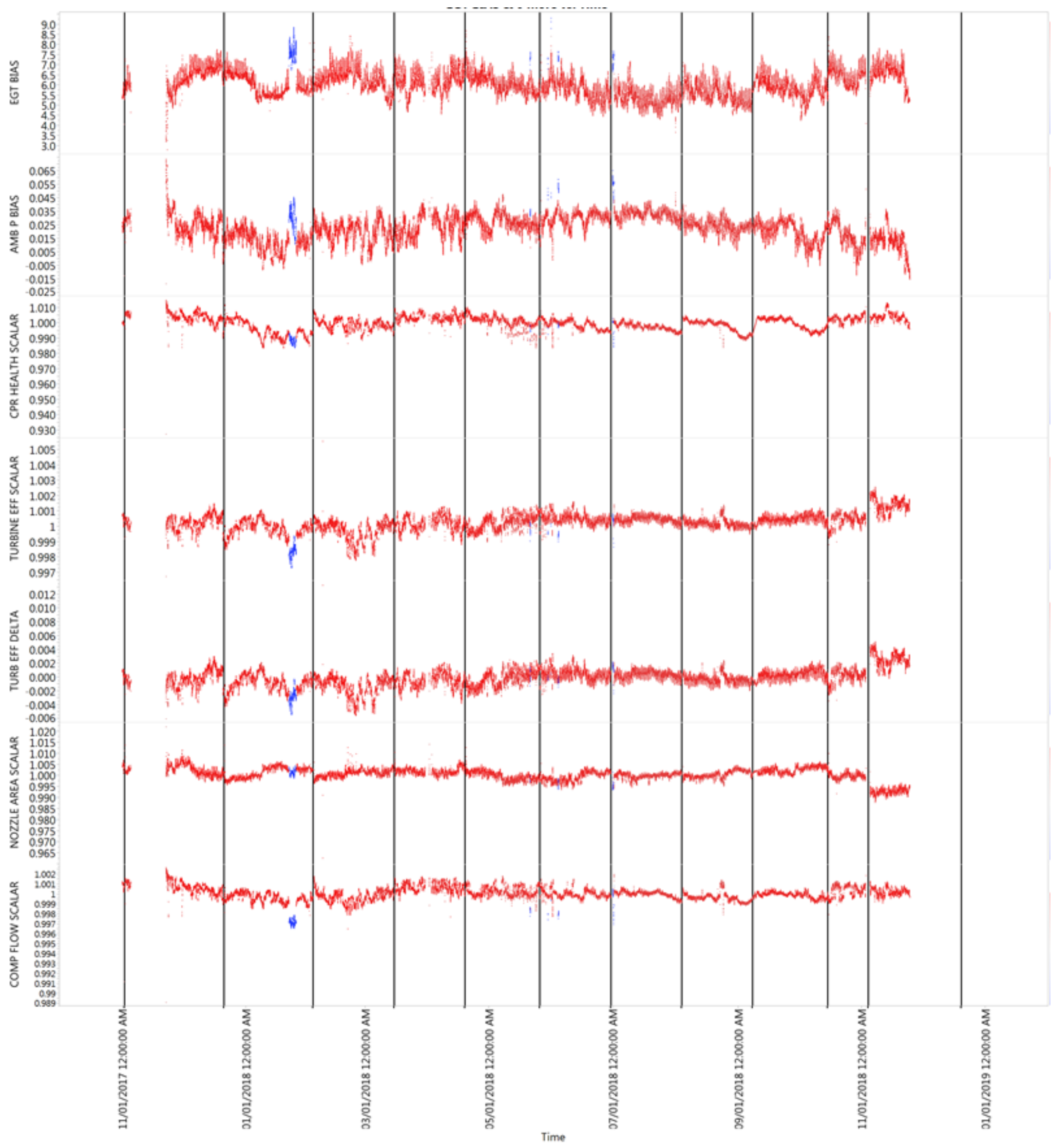
Estimating Water Wash Impacts

- Plot shows one year+ of compressor health parameters
  - Vertical lines show offline water washes
- Can clearly see sawtooth pattern from offline washes
- Used Digital Twin to Predict potential power recovery from wash



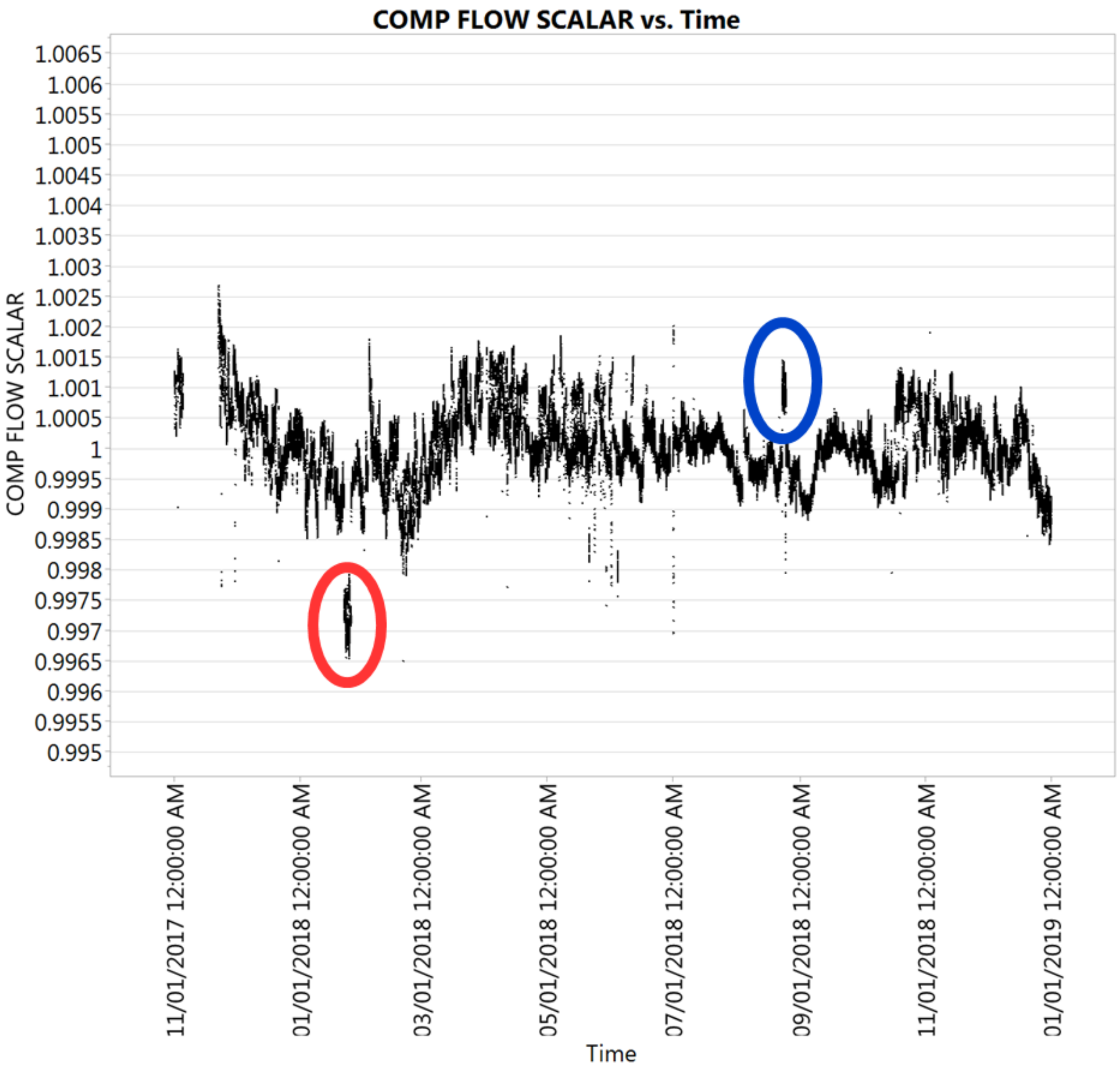
Fault Diagnostics (2020 Reports)

- All Virtual Sensors – 7EA with Virtual Sensor Excursion



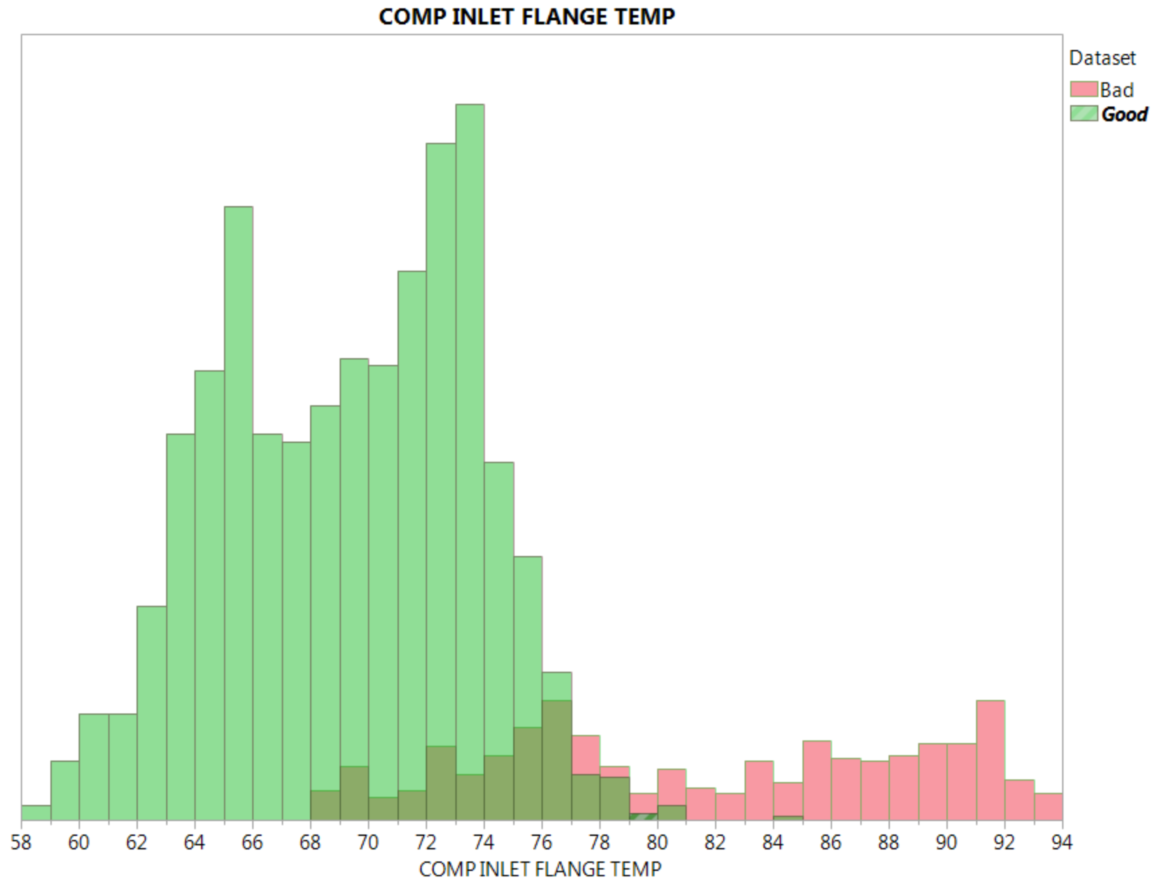
Fault Diagnostics (2020 Reports)

- Virtual Sensor 7EA – Compressor Anomalies

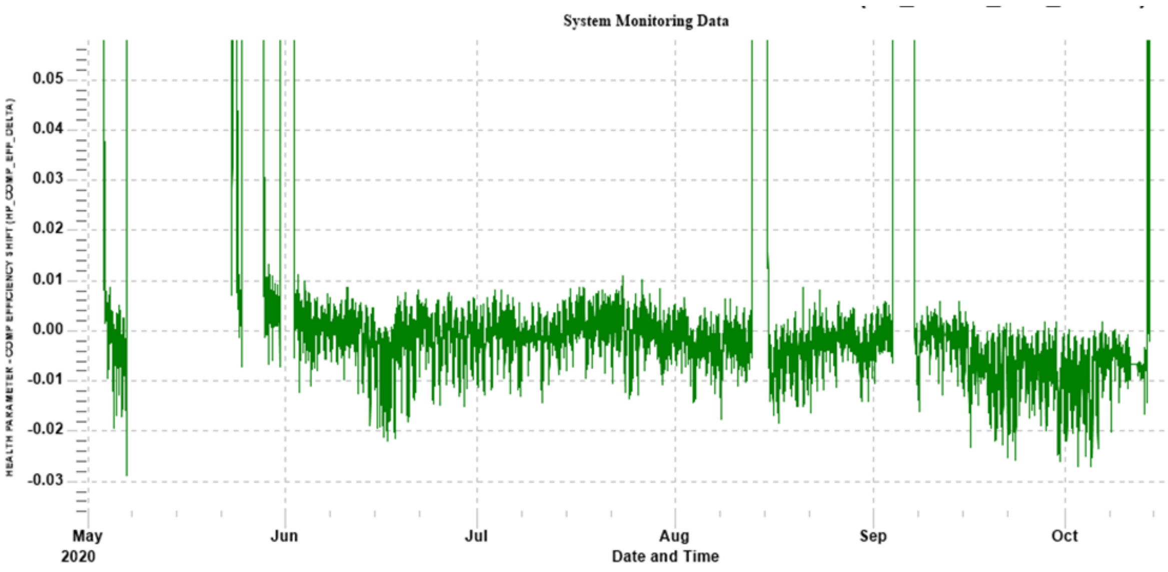


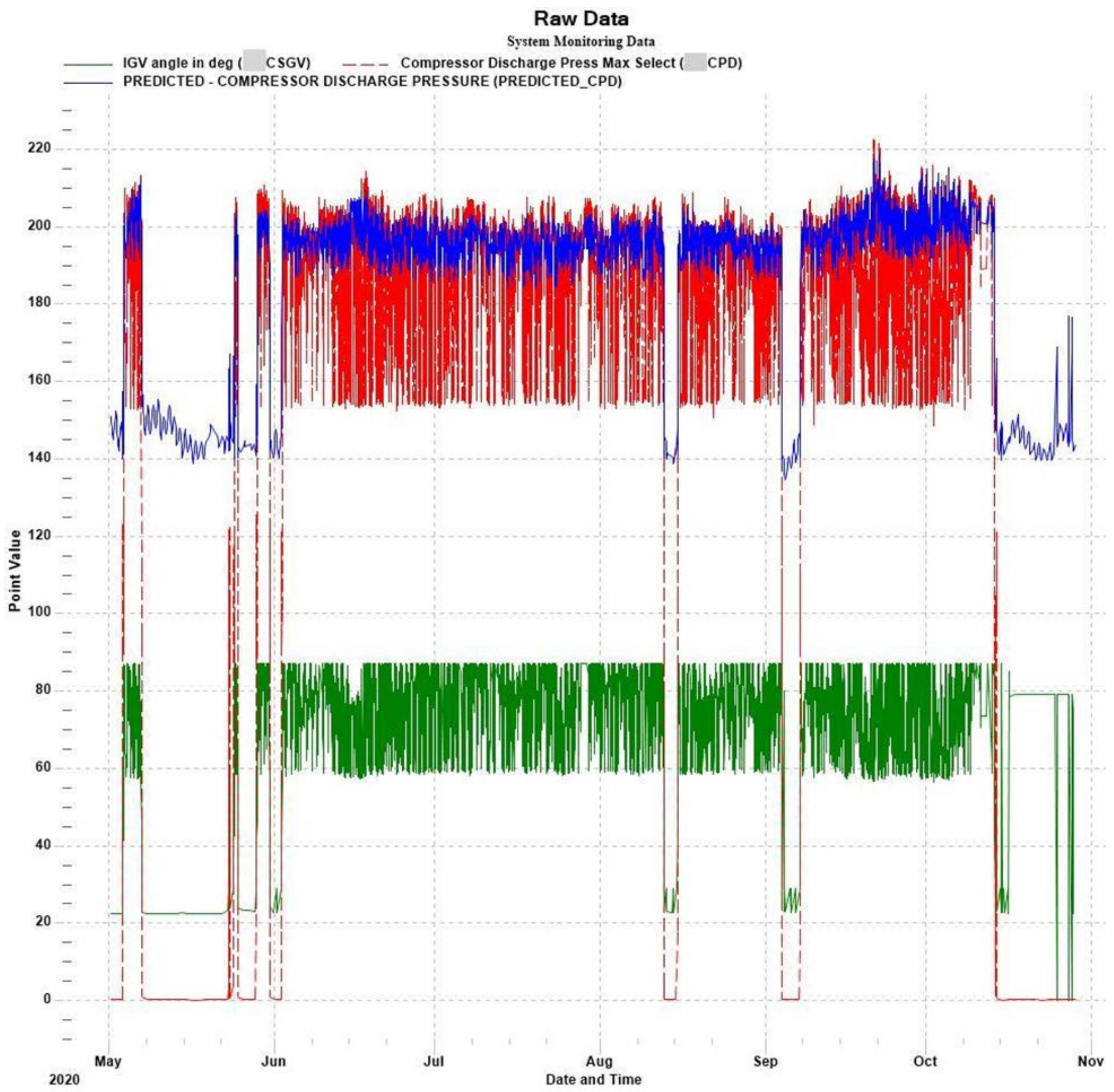
Fault Diagnostics (2020 Reports)

- Investigation of Performance Excursion for Compressor Inlet Temperature



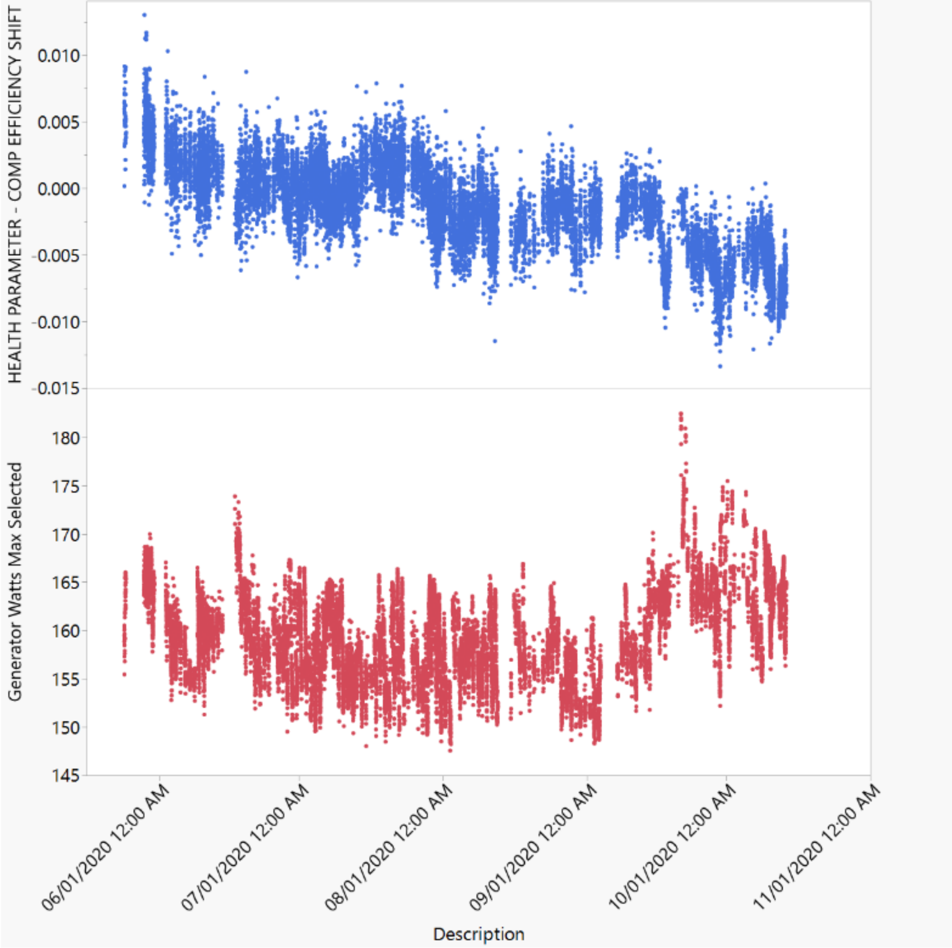
Integration with APR (2021 Turbo Expo)

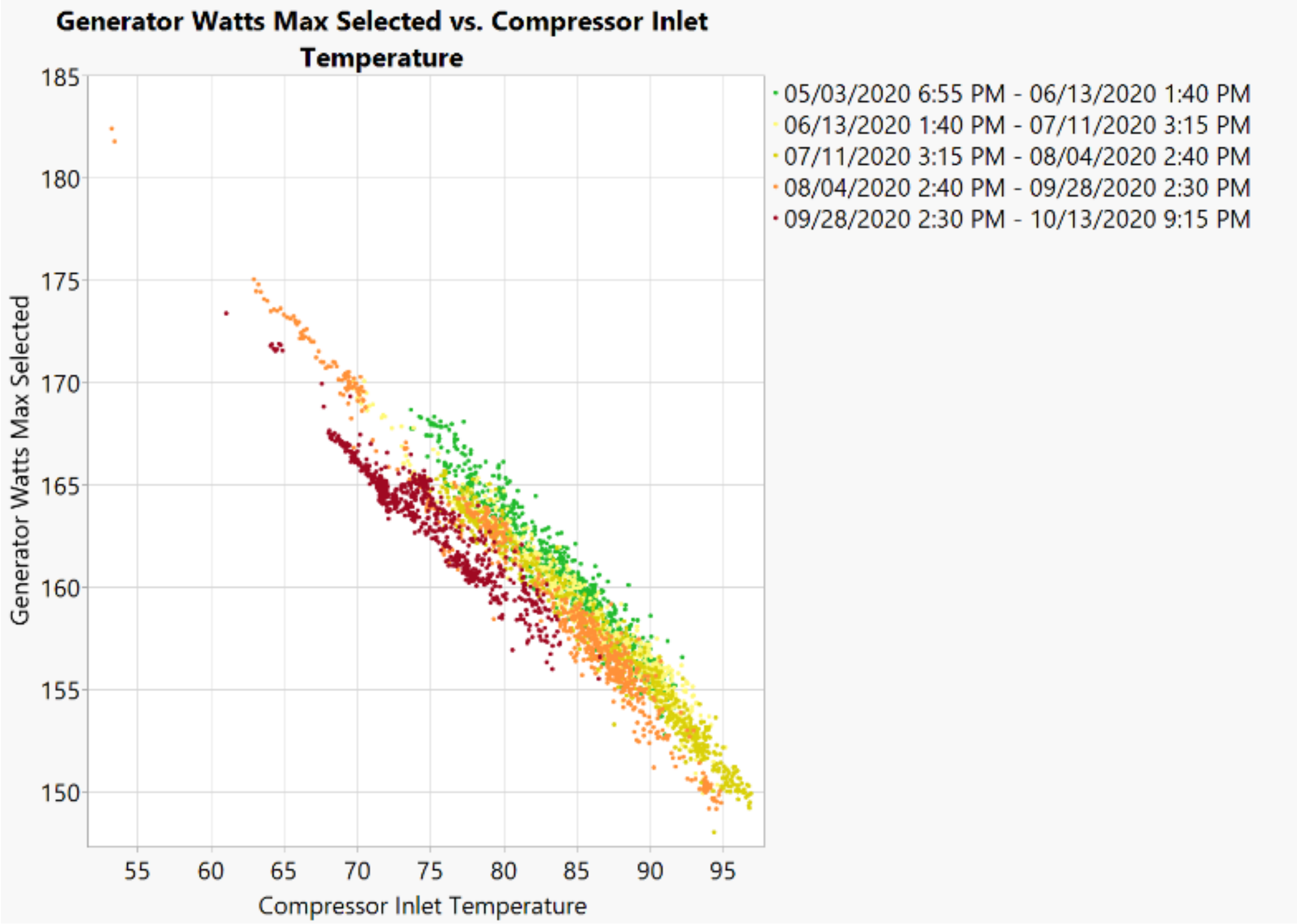




Power Loss Due to Compressor Degradation

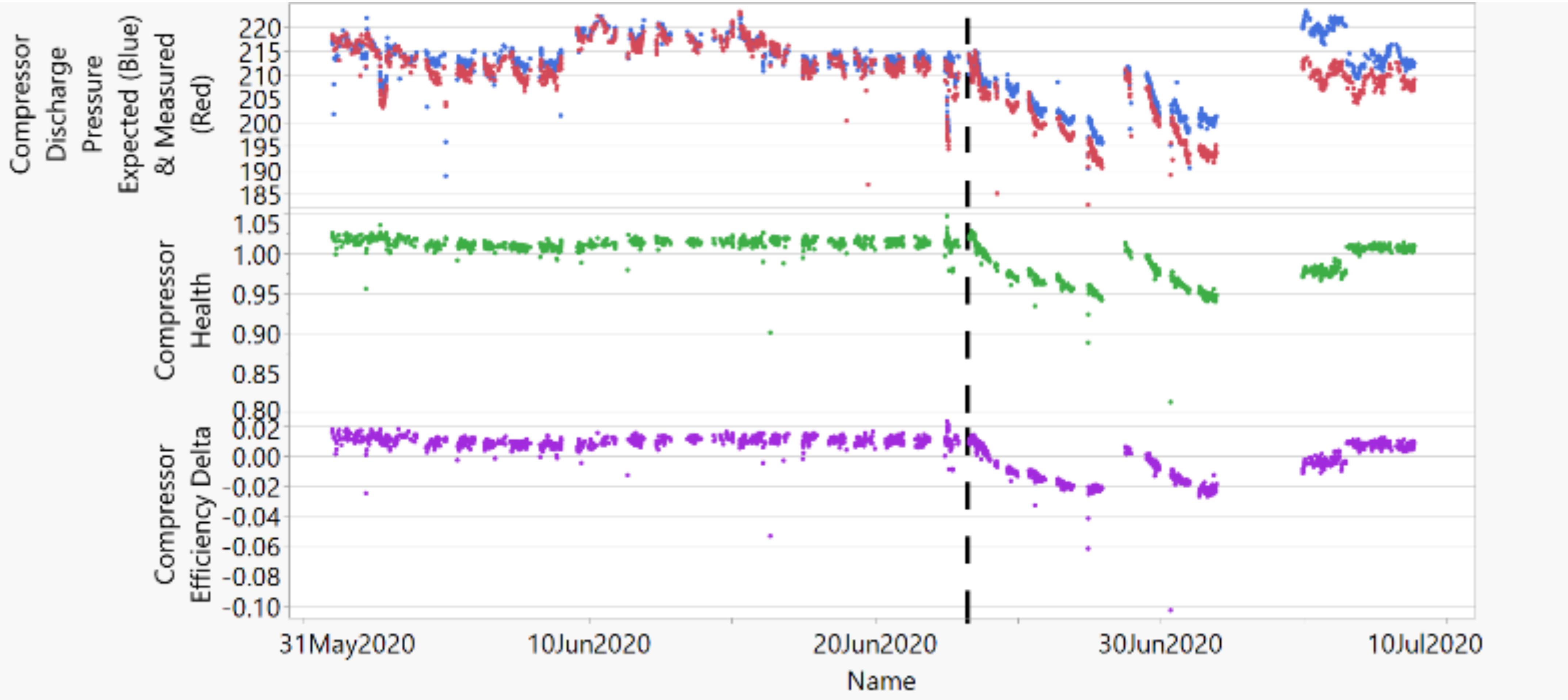
- Using Compressor Health parameters helped identify capacity degradation and to eliminate other causes





Compressor Liquid Fouling Event

- Liquid foreign substance immediately showed rapid degradation in compressor metrics



Post Major-Outage MW Reduction

- Digital Twin comparison of compressor discharge pressure alerted to decrease in CPR after major outage
- Expected DT MW was compared before and after – identified 1 MW reduction in output – cause still unknown, but verified through additional analysis