



Panel Discussion Notes

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Duke Energy - M&D Center

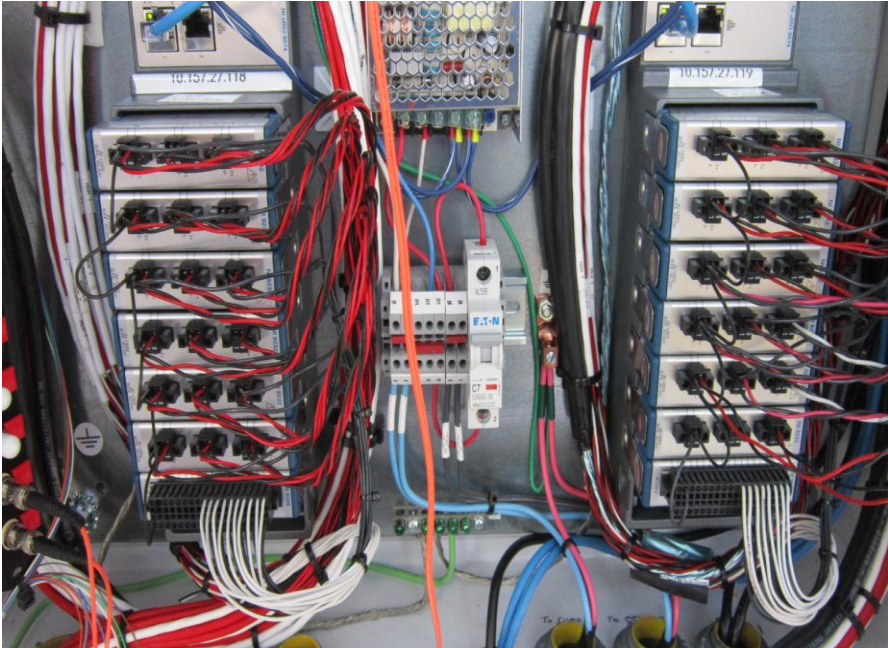


What's Available Now? In Use At Duke



- **First Principles Models – GP Strategies EtaPRO**
 - Fully commercial technology
 - Implemented on 43 units at Duke
 - Virtual Plant allows “what if”. Provides calculated data to component monitoring.
 - Controllable Losses. Compares real time actual performance to target.
- **Advanced Pattern Recognition**
 - Fully commercial technology
 - Fully Implemented at Duke across Fossil Hydro (approx 250 units)
 - Virtual sensor
 - Condition based alarming
- **Advanced Data Infrastructure and visualization – Smart Gen Program with National Instruments**
 - Detailed visualization of hi rez engineering data (vibration, EMSA, MCSA)
 - Infrastructure to install new sensors at low marginal cost
 - Microsoft Power BI for visualization of data

Smart M&D - Typical I/O Enclosures & cRIO



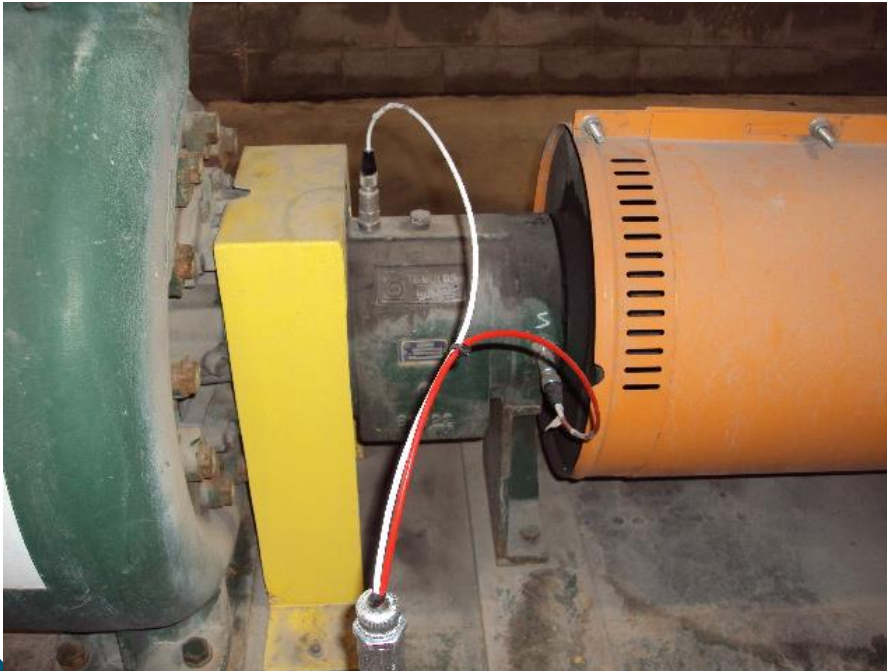
Smart M&D - Scope of Monitoring

- Generators
- Steam Turbines
- Combustion Turbines
- Motors
- Pumps
- Fans
- Transformers
- Iso-phase Bus Ducts
- Electrical Buses



Smart M&D – BOP Vibration

- Accelerometers provide overall vibration and temperature
- Low cost and robust sensors
- Widely deployed where no sensors were deployed before



Online Transformer Monitoring

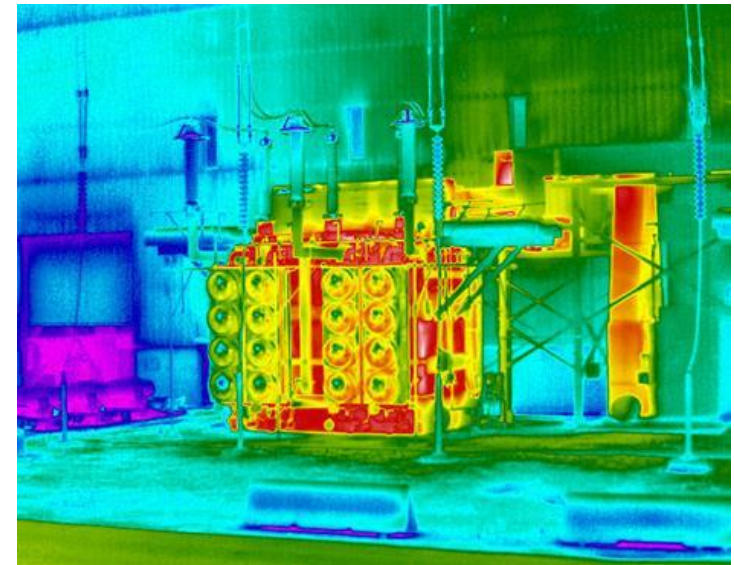
Transformer Monitoring

Dissolved Gas Analysis (DGA)

Temperature Monitoring – Bushings (Infrared Thermography)

Temperature Monitoring – Oil and Windings

Electromagnetic Signature Analysis (EMSA)



Online Transformer Monitoring

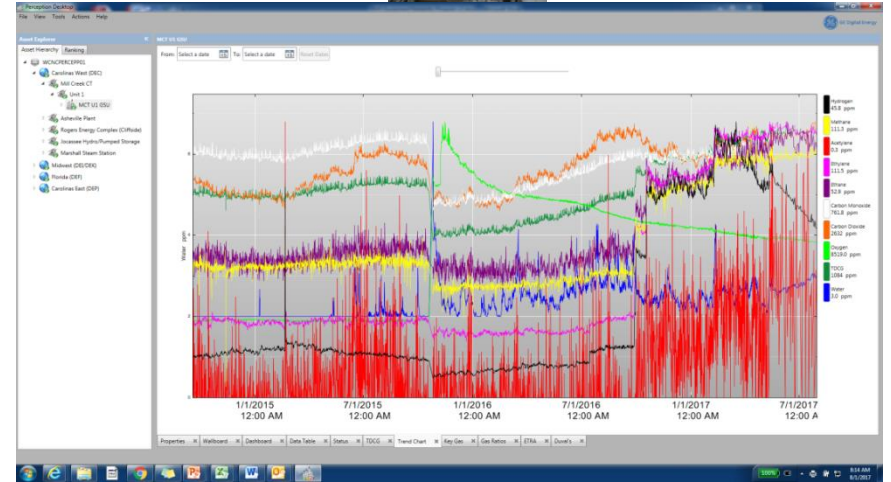
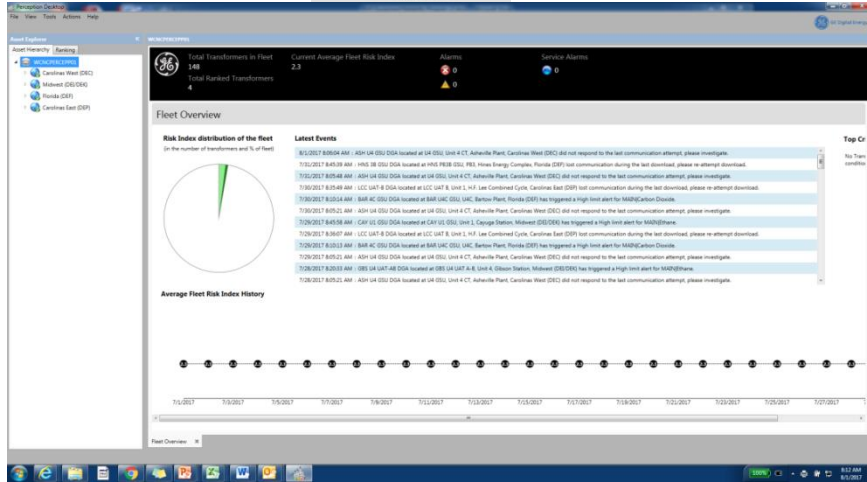


- Technologies
 - Dissolved Gas Analysis (DGA)
 - Temperature Monitoring – Bushings (Infrared Thermography)
 - Temperature Monitoring – Oil and Windings
 - Electromagnetic Signature Analysis (EMSA)



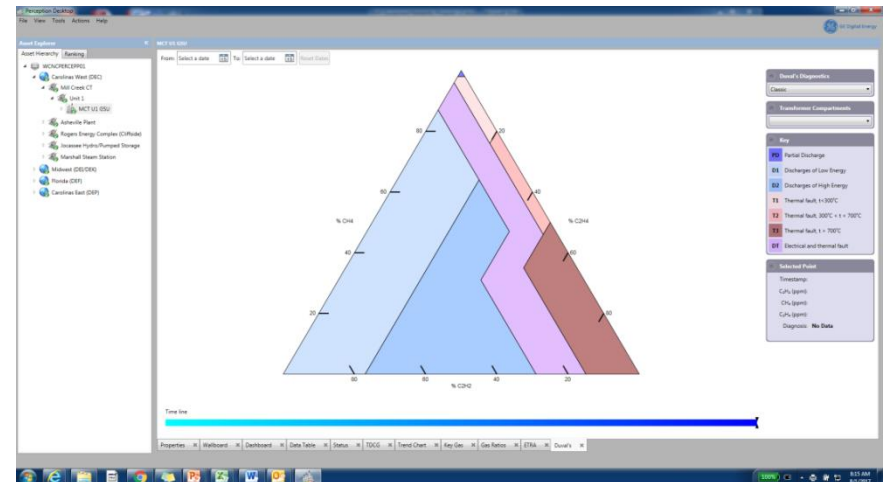
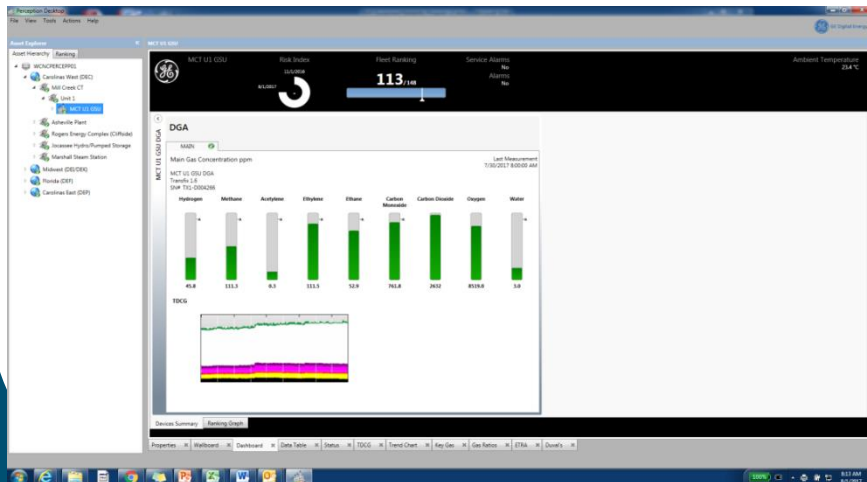
Fleet Overview

Main Gas Concentration PPM - Trend



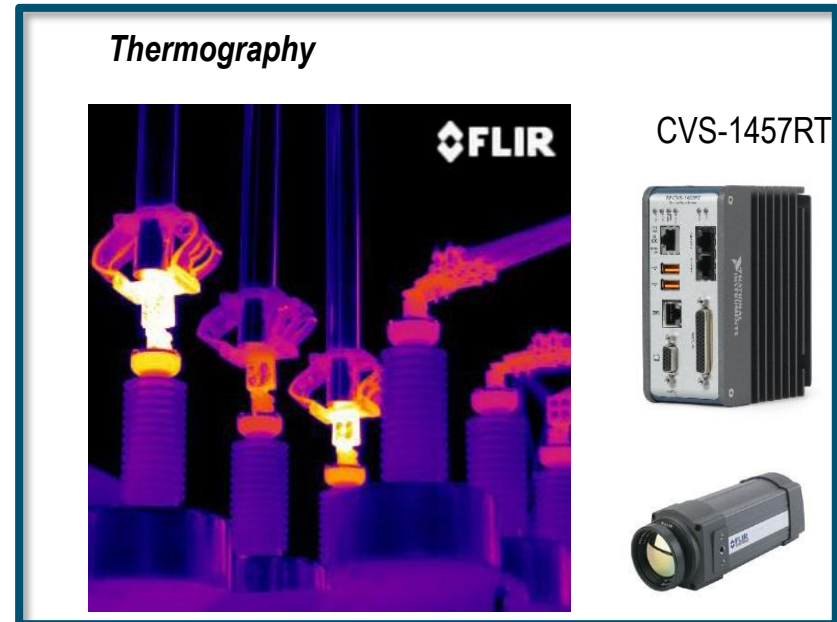
Main Gas Concentration PPM

Duval's Analysis



Smart M&D - Infrared Thermography

- FLIR A65 IR Camera
 - Network connection
 - POE
 - Low cost
- National Instruments 1457 CRIO
 - Network connection
 - Dual Gig E Inputs

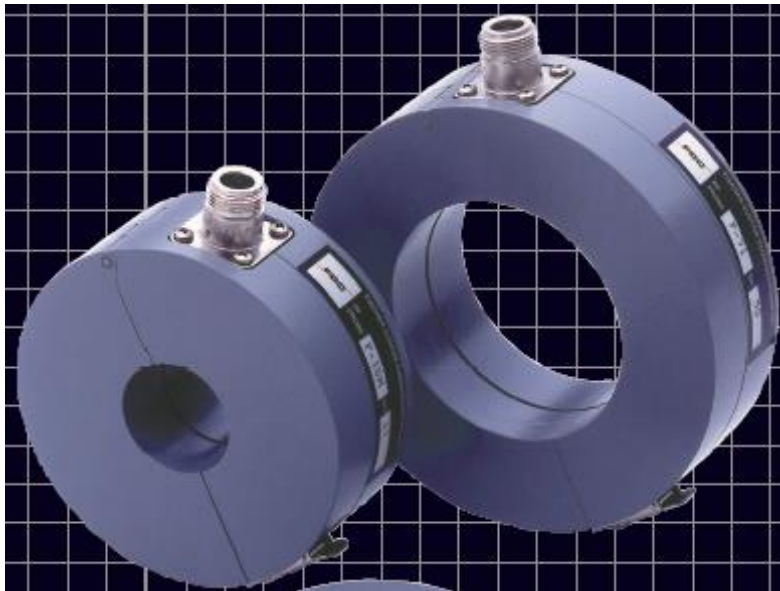


- RF Temperature sensor
 - Lug mount
 - RF signal to a receiver mounted in same panel
- Fiber Optic Temperature sensor
 - Utilizes Fiber-Bragg gating technology
 - Can measure temperature at many locations on a single strand
 - Can be up to a kilometer long

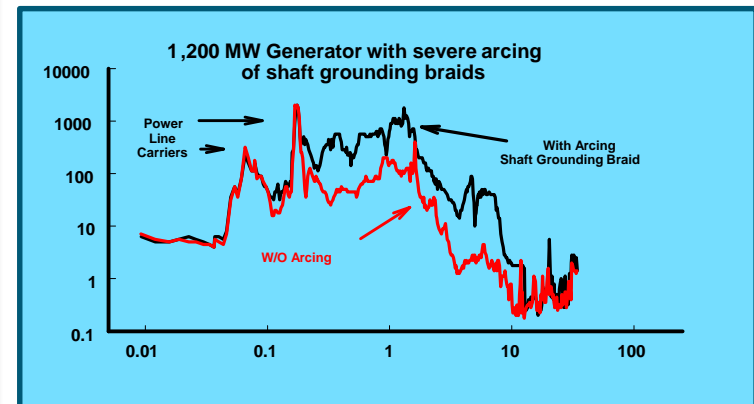
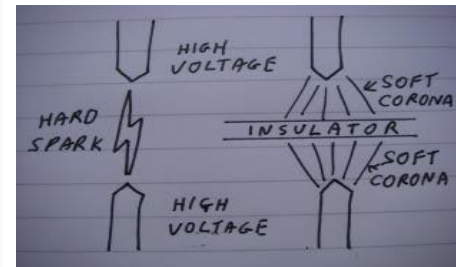


Smart M&D - Electromagnetic Signature Analysis

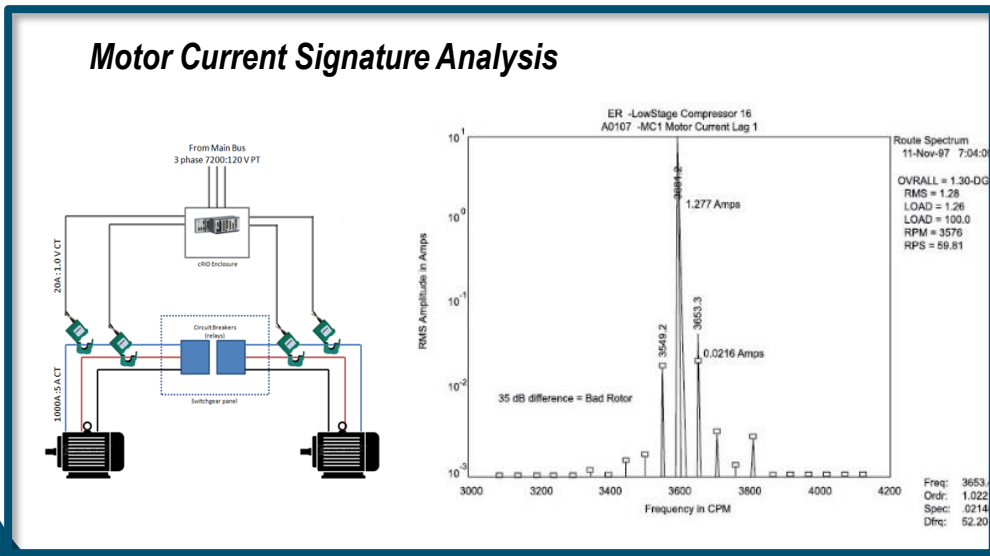
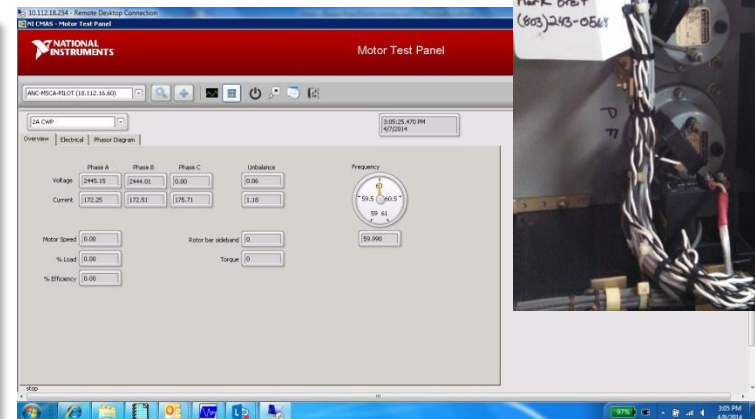
- Monitors generators, transformers and other >13.6KV equipment
 - Provides early indication of insulation and connection degradation
 - Utilizes the ground leads and equipment housing as antenna



Electromagnetic Signature Analysis



- Monitors motors with accessible CT leads
 - Provides early indication of rotor and electrically detected issues
 - Utilizes a low cost split core CT for quick installation
 - Calculated motor parameters such as torque, phase angle etc

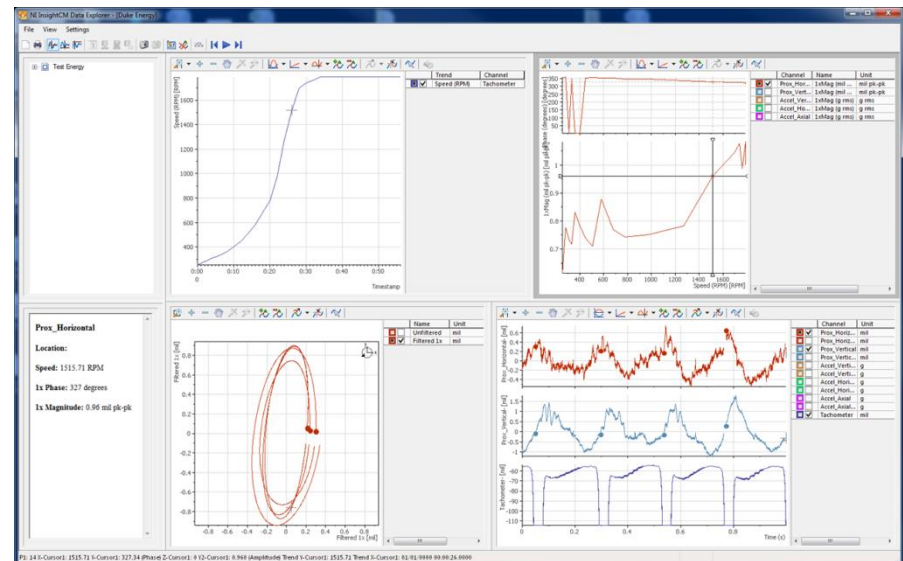
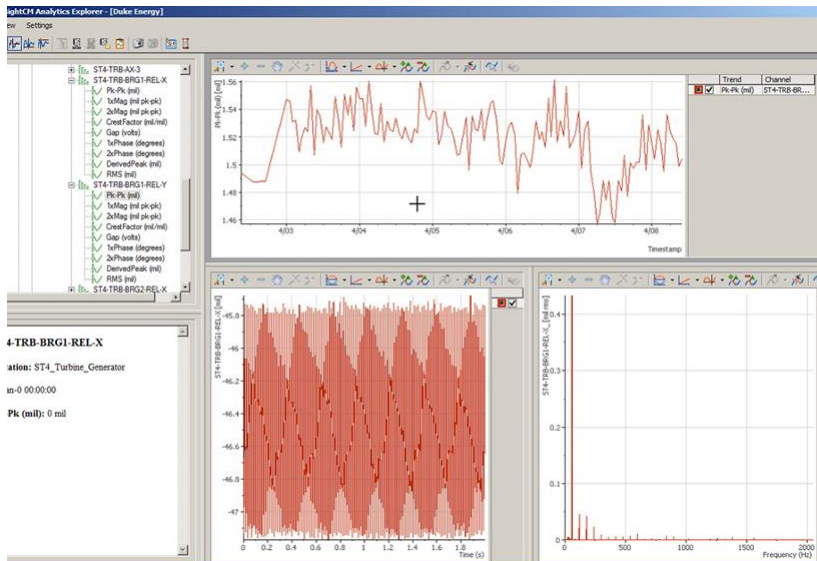


- Leak Detection
 - CT enclosure (piping, casing leaks)
 - Boiler/HRSG (tube leaks)
- Electrical Bus Monitoring
 - Bus monitoring for arcing, corona
- CT Foreign Object or Domestic Object Detection (FOD/DOD)
 - Used to hear impacts in a CT caused by foreign or domestic debris

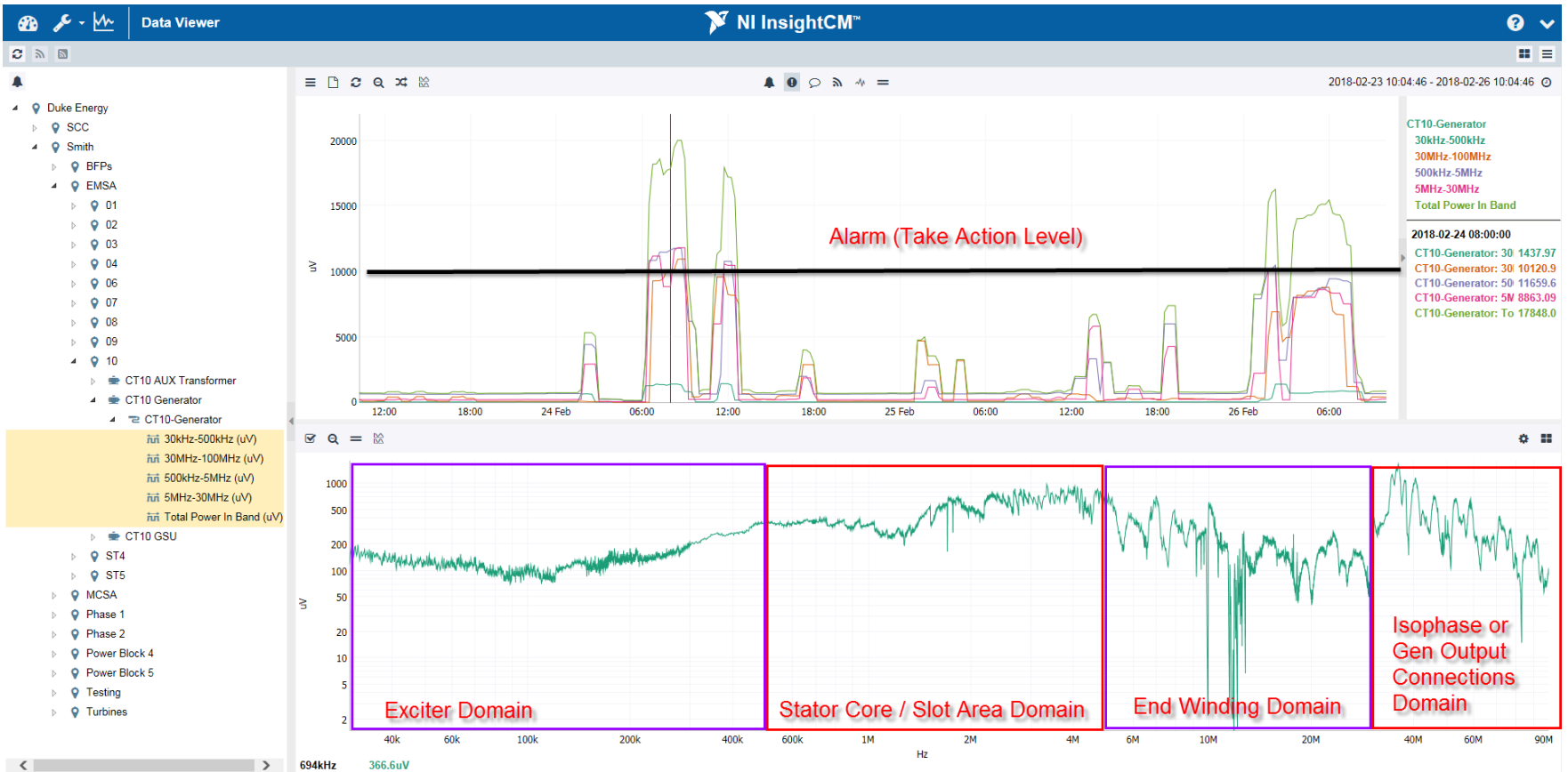


National Instruments “InsightCM” Software

- National Instruments has developed condition monitoring software to provide:
 - A user interface for various sensors
 - Data to PI for M&D Center monitoring
 - NI software & hardware will accept multiple input types
 - Looking for other vendors to partner and develop new sensor inputs



EMSA Regions of Interest and Interpretation



Limitations of Existing Technology

- APR generates many false positives. This requires screening before notifying the plants.
- No proven technology to monitor transient performance. (Startup/shutdown and load changes are modes ripe for equipment damage).
- Maintaining and training models is a constant effort.
- Failure Mode Effects Analysis does not integrate well with APR.
- We are implementing rule-based, decision-tree diagnostics in the first principles system. But the application is limited to major focus areas at this time.
- Diagnosis and time to failure (or better yet – mission viability) are not available.
- We do not know how to interpret EMSA or MCSA data

WHAT IS THE BEST APPROACH FOR M&D?

finding the right balance

Top Down

Data Driven

APR

SparkPredict

SME's needed for
unknown events

Train on events

Engineering at the end



Bottom Up

Engineering Driven

APR (trains on normal)

PHMUG

GP Strategies Predictor

DEI – Dynamic RUL

Train on known failure
behavior

Engineering up front

What's the Optimal Approach?

Goal – less human more machine capability

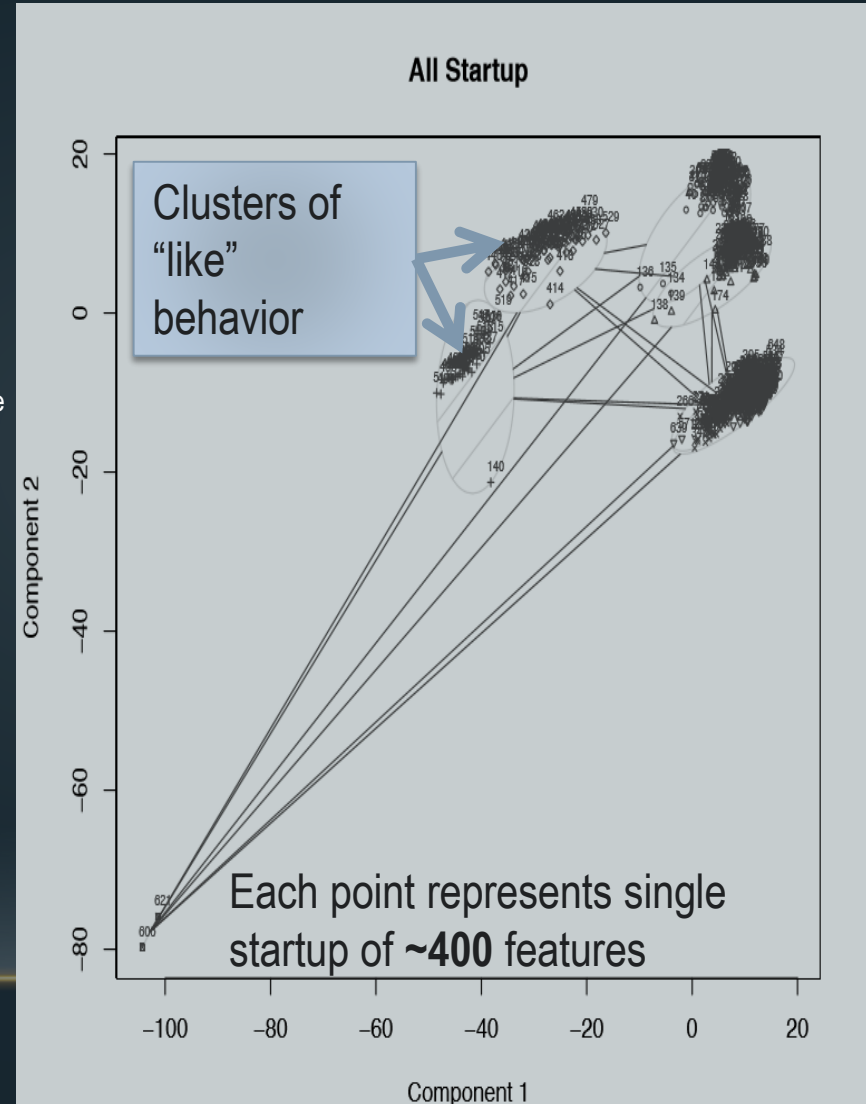
May be combination of approaches

Need a universal interface and fault library

Install Impact – Care & Feeding

UNSUPERVISED STATE DETECTION; JUST THROW DATA AT IT AND SEE WHAT IT FINDS...

- Cluster Gas Turbine startups via **unsupervised learning** (i.e. we don't know the "labels")
- Analysis of 1300 Events
- Utilizes National Instruments cRIO data (TDMS) for **vibration** and **speed**
 - ~15-20 Vibration Channels/Turbine
 - ~10 Features Calculated on cRIO
 - ~10 Features Engineered by SparkCognition engine
 - ~**400 Total Features** Analyzed per Startup/Coastdown



KEY FEATURES DESCRIBING THE EVENTS WERE SPEED AND TIME

sparkpredict

Ingest Alerts Assets

Filter Results

Severity	Correlation Level	Site	Area	Equipment	Asset ID
●	7	Smith	Phase 1	CT2	
●	21				45D03
●	1	Smith	Phase 1		802F145D03
●	12	Smith	Phase 1	CT2-PNL-TGVDM01	3322-00802F145D03
●	8	Smith	Phase 1	CT2-PNL-TGVDM01	3D93B3C3-6995-11E4-9E6A-00802F145D03

Expand

All Startup

Each point represents single startup of ~400 features

Component 1

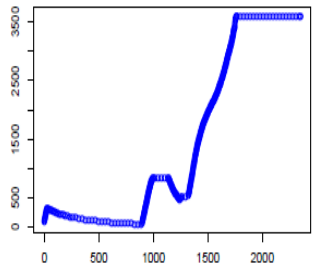
Component 2

Component 3

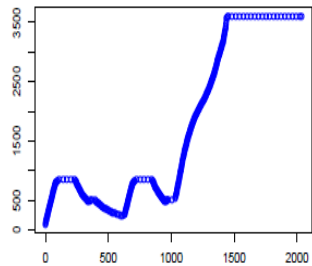
Correlation levels are generated automatically. Sorting by levels identifies critical events

THE TOOL WAS FINDING OPERATING STATES ... STARTUPS

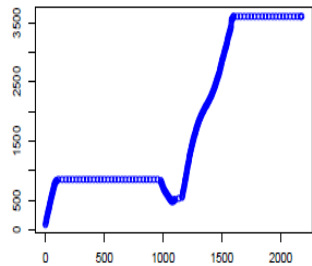
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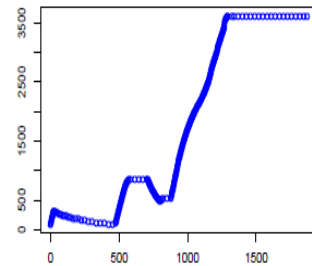
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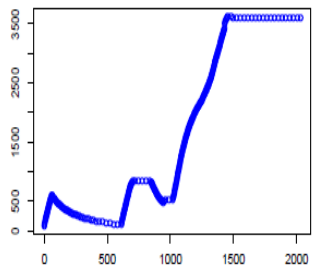
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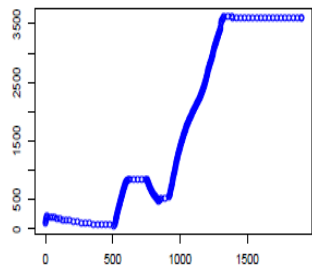
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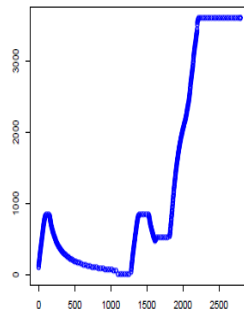
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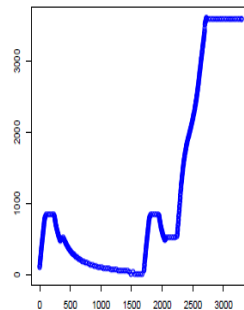
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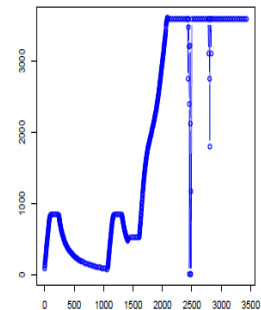
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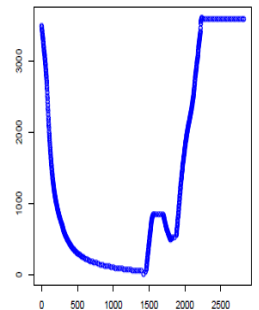
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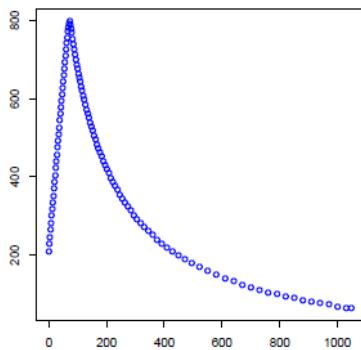


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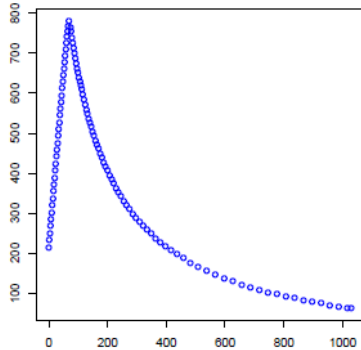


... COASTDOWNS...

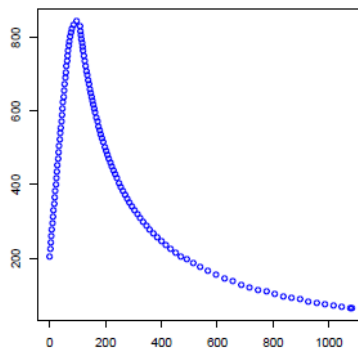
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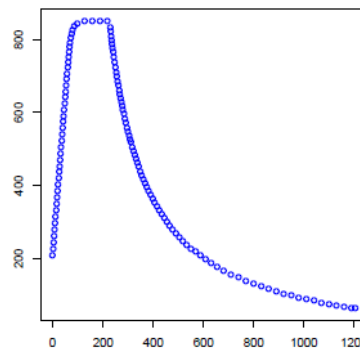
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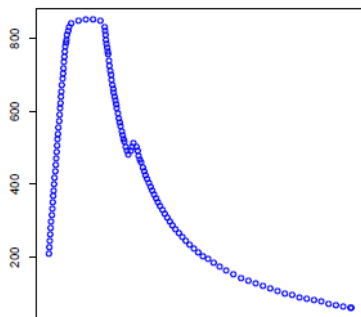
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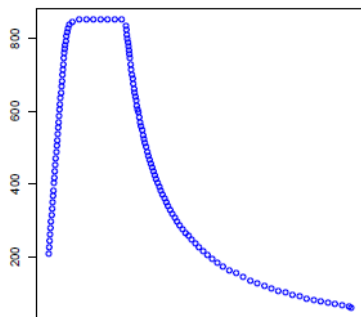
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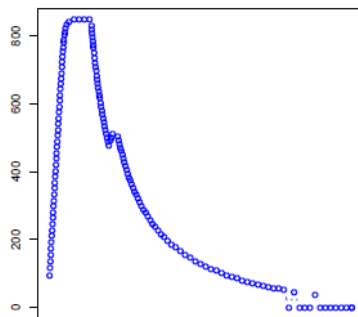
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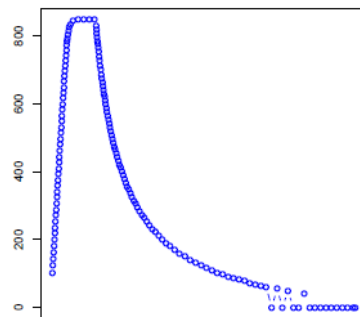
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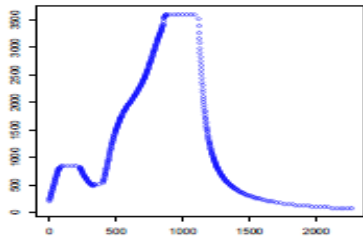


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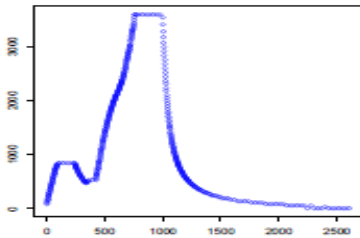


... STARTUPS ATTACHED TO COASTDOWNS

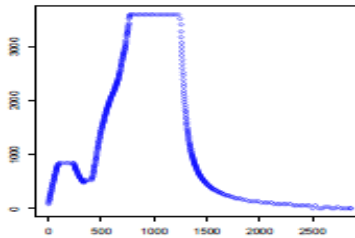
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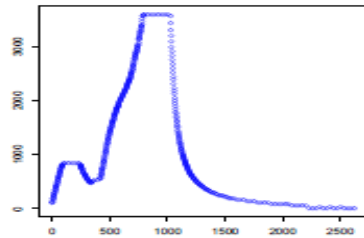
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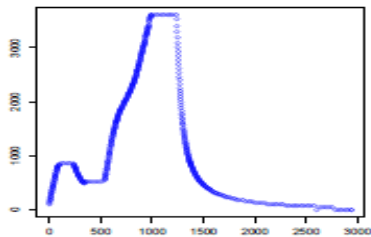
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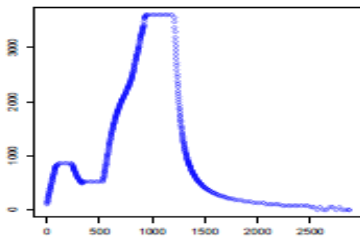
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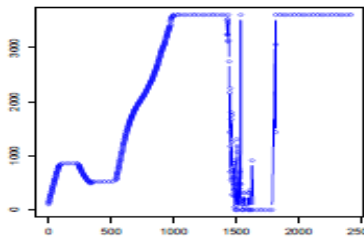
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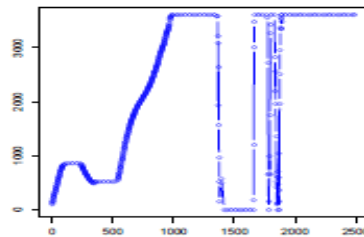
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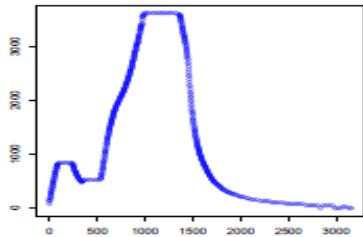
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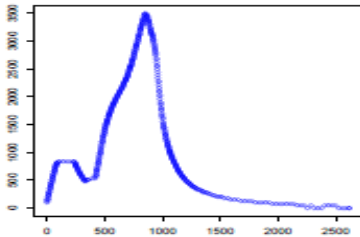
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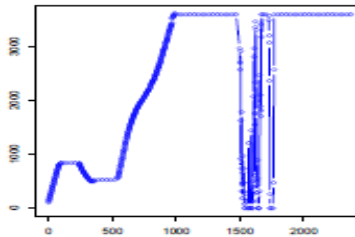
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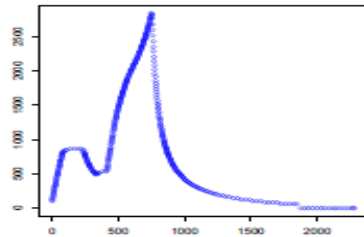
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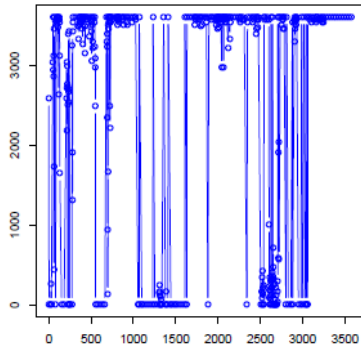


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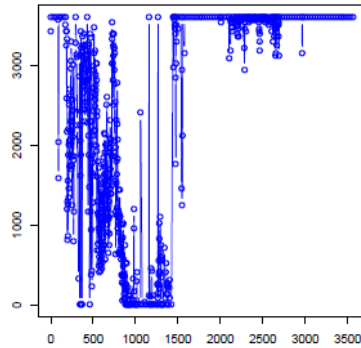


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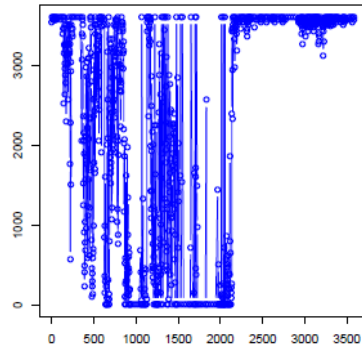
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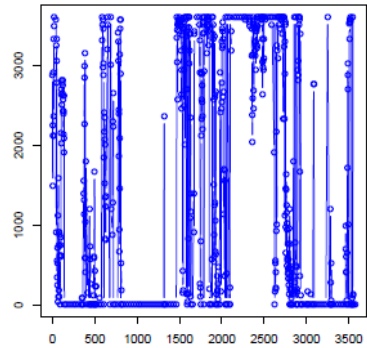
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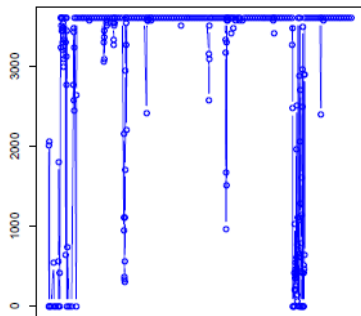
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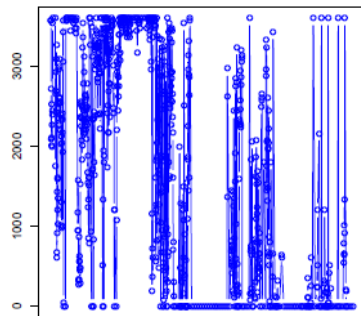
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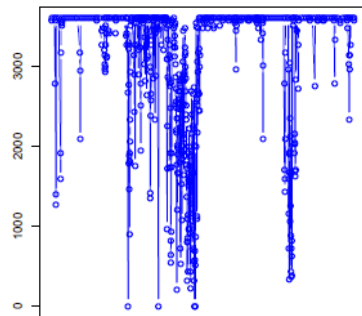
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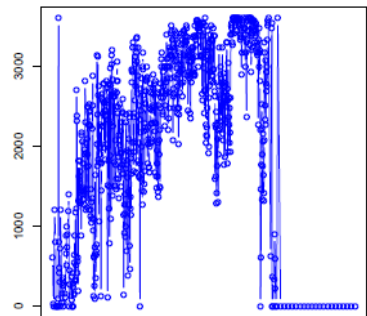
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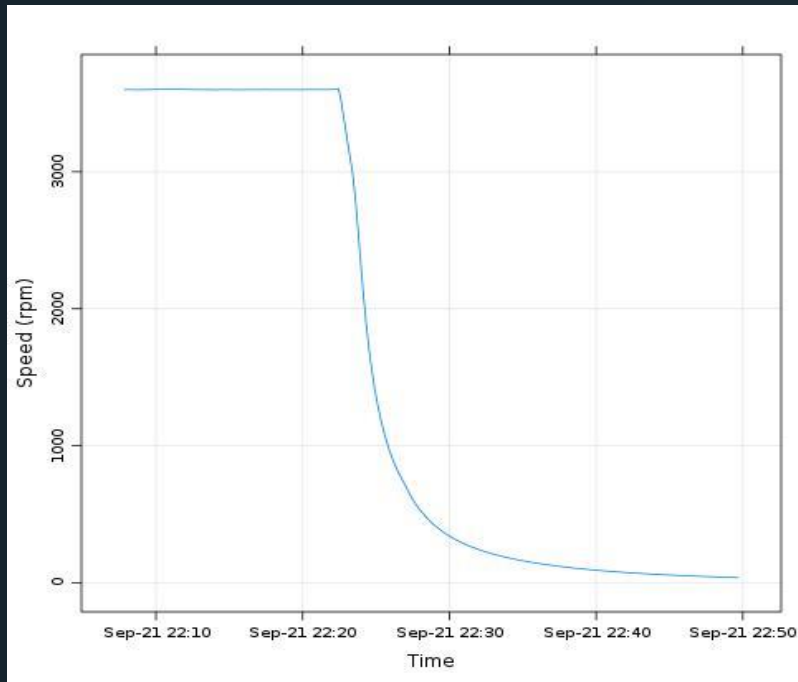


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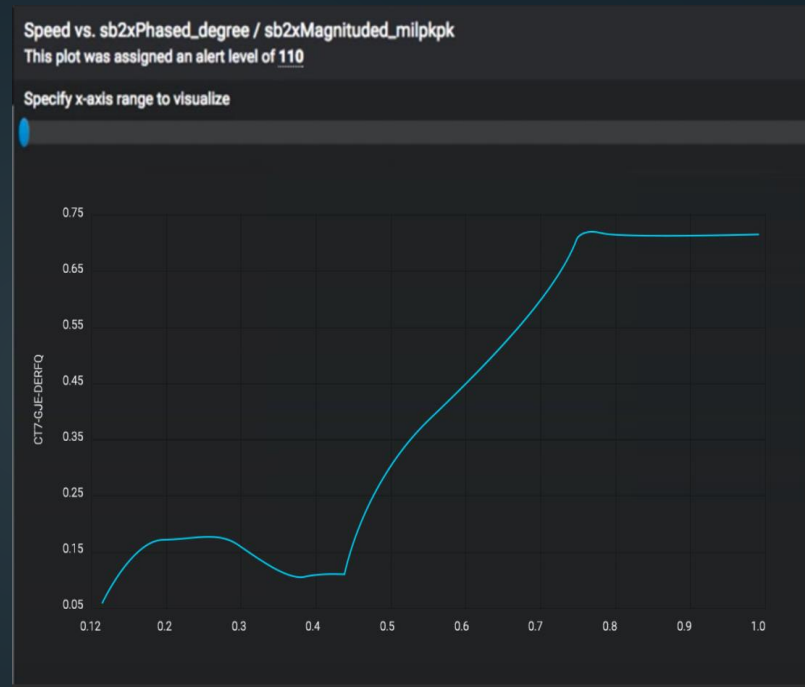


FIRST IDENTIFY THE OPERATING STATE

This is a coastdown

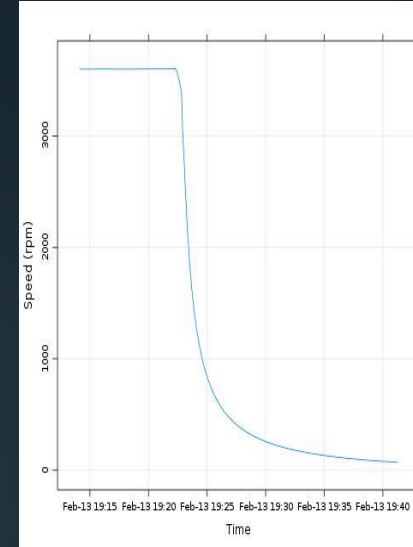
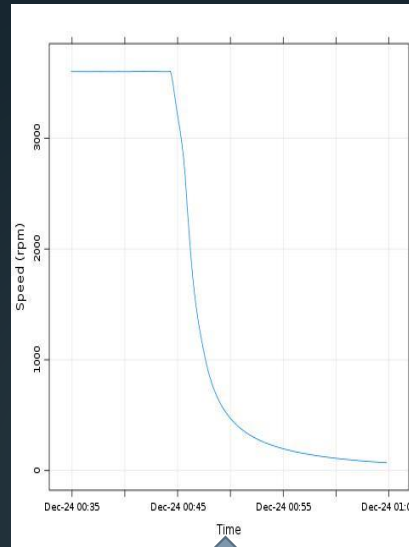
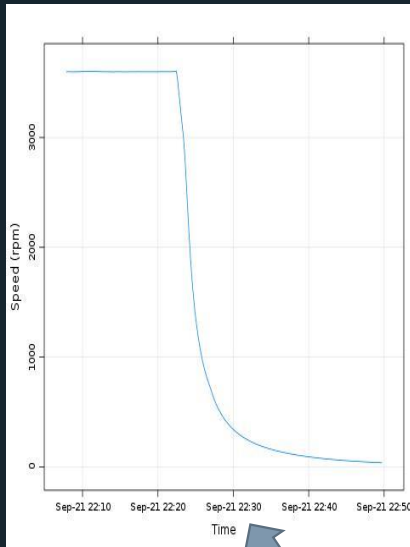


This is a Startup

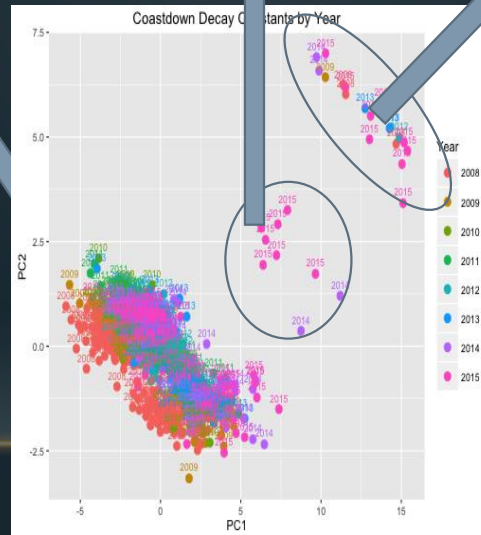


Axis is Speed vs Time

APPLY MORE FEATURES

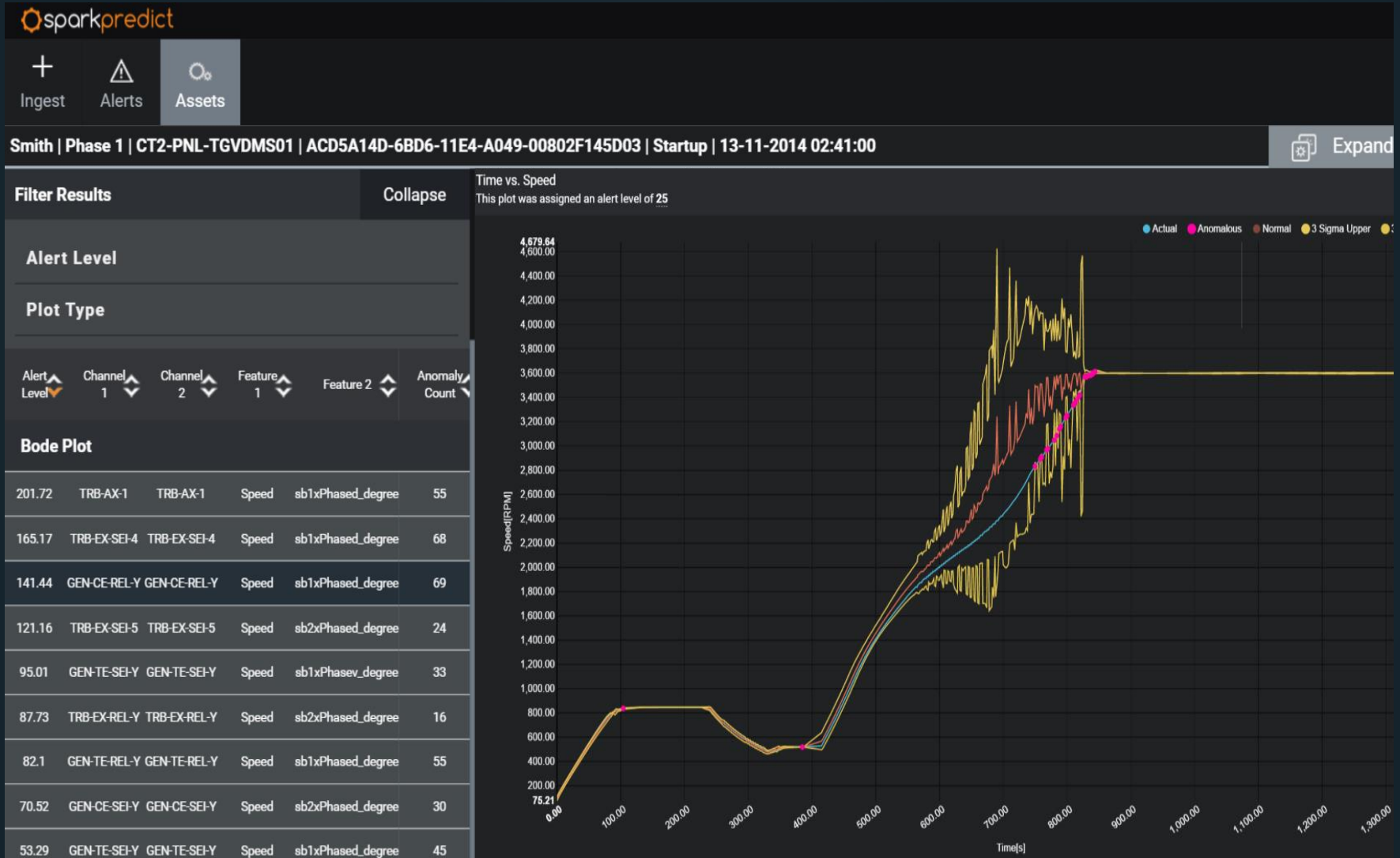


- Now add **thousands** of features/turbine
- Identify new events coming in **real-time**
- **No modeling** required from SMEs to gain insights
- Model keeps **learning** → SMEs can “nudge” model over time.



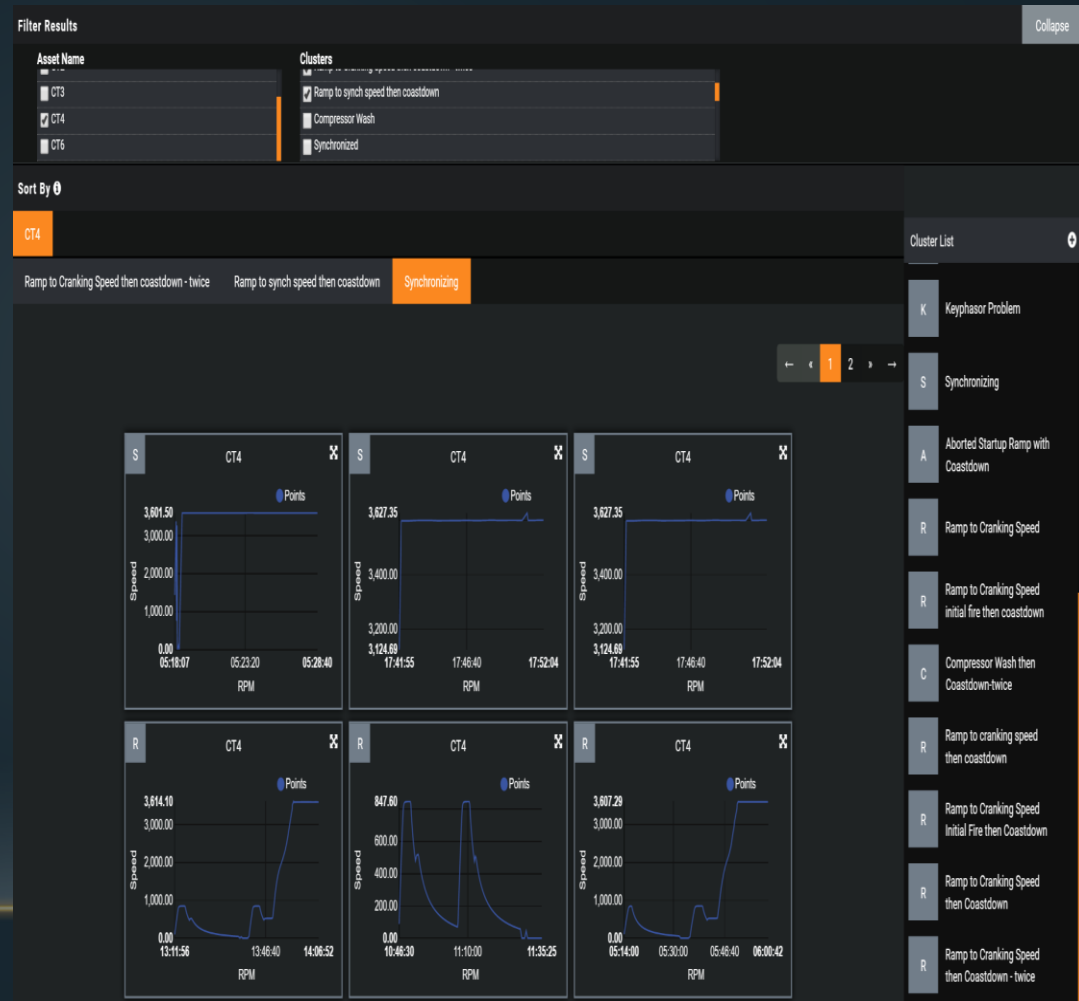
As we add more variables the picture

FIND ANOMALIES - FEATURE CONTRIBUTION AND COMPARE TO NORMAL

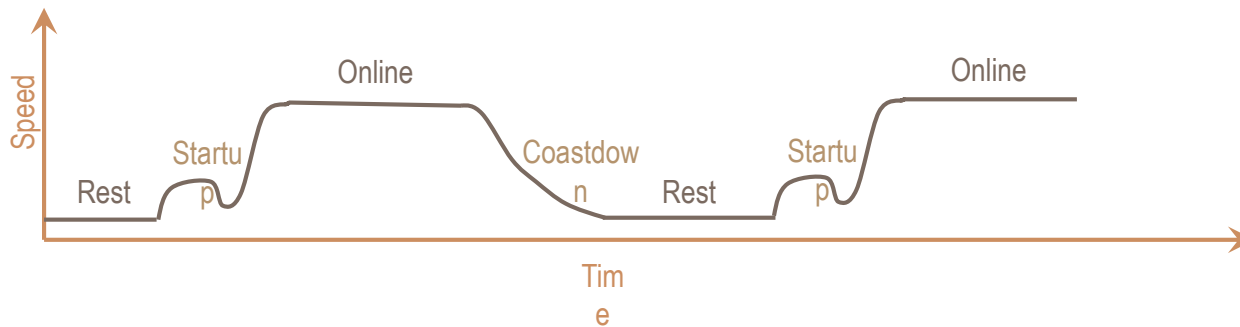


TAKE THE UNSUPERVISED BEHAVIORS AND APPLY SUPERVISED LEARNING

- Classify Gas Turbine transient events via **supervised learning** (i.e. we know the “labels”)
- Automatically classifies multiple operating states
- Ability to utilize and capture SME expertise, then **LEARNS**
- A top down vs bottoms up approach
- Utilizes National Instruments cRIO and OSI PI historian data for vibration and speed



GENERAL EVENT CLASSIFICATION WORKFLOW



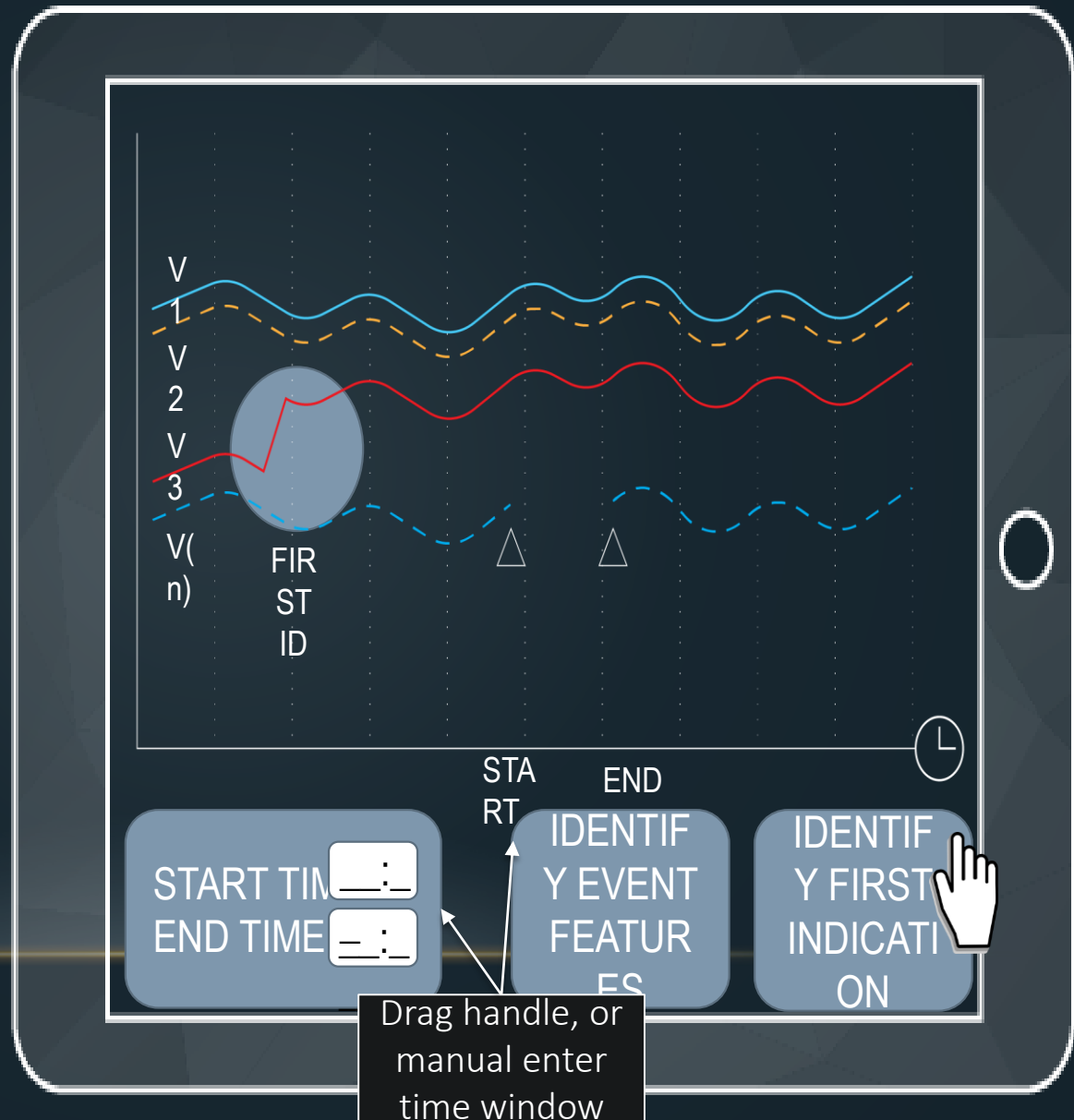
A Day in the life of a Turbine

Order of Event Classification

- Classify the Operating State (every state has an associated thermal vector state that follows)
- Identify unique operating events within the state
- Compare relevant features that describe the event
- Match features to normal behavior in that mode and alarm anomalous events
- Name and store the feature set for identifying future events
- Event library grows over time

Adding and Identifying Known Sets

1. User identifies event time window
2. Tool locates event and identifies relevant features.
3. Interactive analysis tool to validate tool results (same tool we are building to analyze any event)
4. Tool Identifies earliest relevant anomaly that preceded the event. In some events, the first indication and the event are the same...in others they could be separated in time



PROBABILITY DISTRIBUTION OF KEY VARIABLES IN AN EVENT

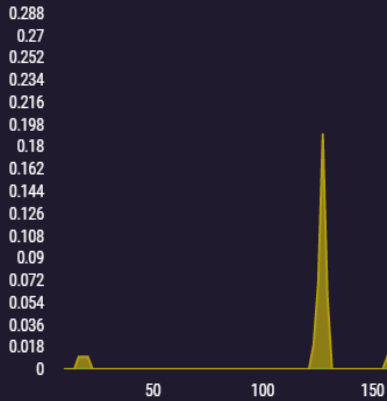
Data Science View

Graph Plotter

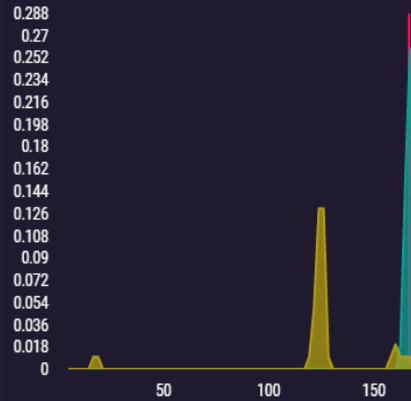
Event Evidence



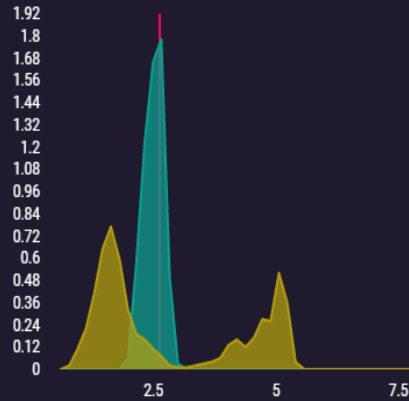
● fullspeed/C2 ● Other Clusters



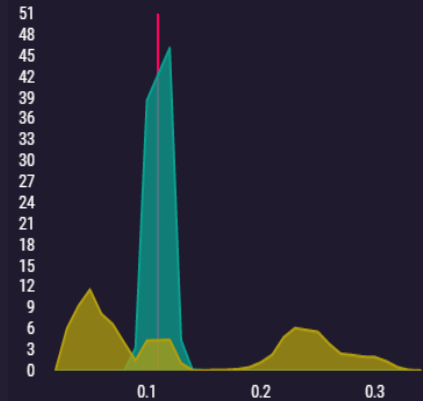
axial_position_sensor_turb_brg_#1_-_x



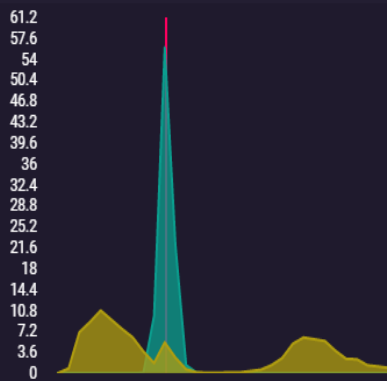
axial_position_sensor_turb_brg_#1_-_y



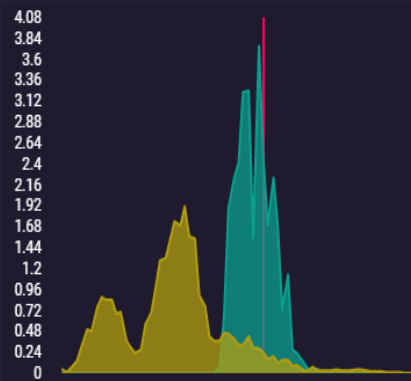
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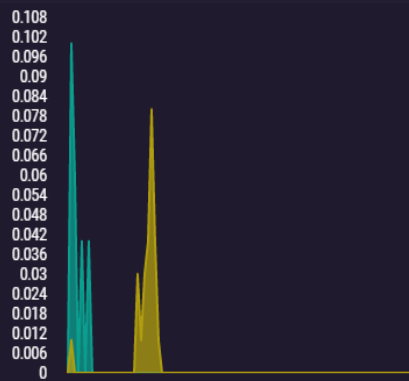
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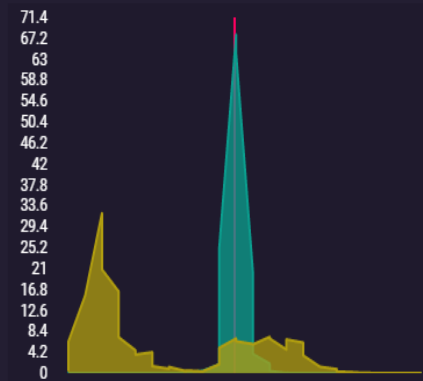
axial_position_sensor_turb_brg_#1_-_x



axial_position_sensor_turb_brg_#1_-_y



radial_vibration_sensor_turb_brg_#1_-_x



radial_vib_sensor_1x_magnitude_turb_brg_#1_-_x

CURRENT APPLICATION CAN ASSIST WITH ROOT CAUSE ANALYSIS

- ▶ Each dot here represents a separate startup for the turbine
- ▶ Startups are identified automatically and are compared only to other startups
- ▶ We combine thousands of variables at different collection rates
- ▶ Classes combine events that look like other events in the same class
- ▶ Anomalies are events that do not resemble events in any of the other defined classes
- ▶ Over time, a portion of the anomalies can be used to define



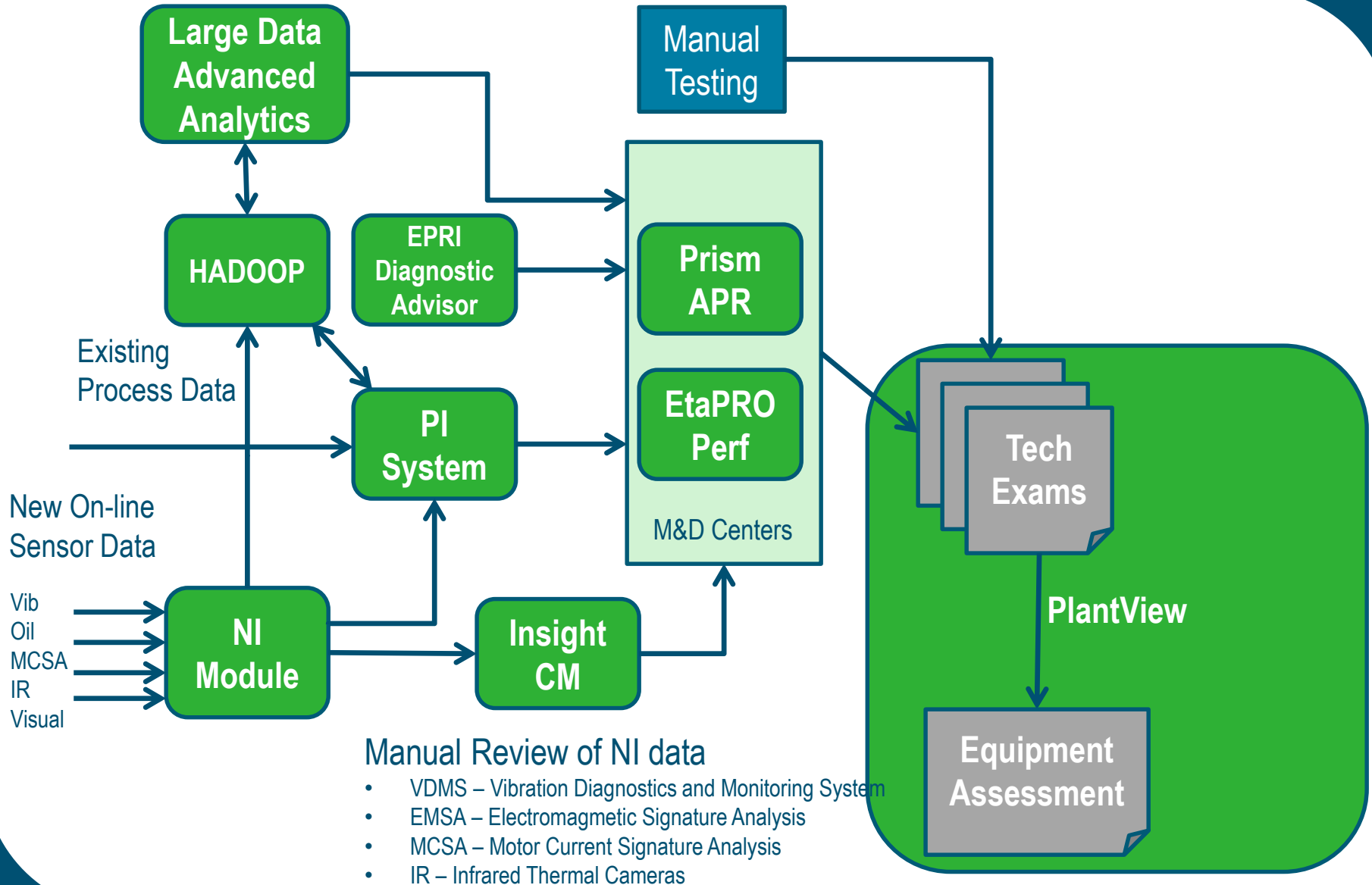
KEY TAKAWAYS

- Duke Energy has a well established M&D Center to monitor Fossil and Hydro assets
 - First Principles Thermal Performance Monitoring
 - Statistical Pattern Recognition for anomaly detection
 - Advanced sensor development and infrastructure
- M&D is replacing manual “rounds” but the rapid growth exceeds available resources
- Better analytics would screen false positives, diagnose potential causes of failure and estimate remaining useful life
- There are several approaches to advanced analytics but a clear path for utilities has not been demonstrated
 - User interfaces and workflow integration need to be developed
 - Proof of concept and pilot evaluations/demonstrations are needed
 - FMEA and fault signature libraries need to be built and integrated

KEY TAKAWAYS

- Moving data to advanced analytics applications is an issue
 - Data security requires end-to-end certification and qualification for anyone who touches the it – especially third parties
 - Legacy historians are not optimized for moving large amounts of data to external users
 - Manual methods of assembling and moving large datasets for analytic POC's is not practical
 - Smart Gen sensors generate widely varying types and amounts of data
- How do we optimize the infrastructure for advanced analytics systems?
 - Smart Gen sensors can generate more data than infrastructure can transmit. How do we optimize the infrastructure at the edge?
 - How do we optimize storage of large datasets? How much data should we keep? What is a good decimation strategy?

M&D Center Data Future Functional Overview



Manual Review of NI data

- VDMS – Vibration Diagnostics and Monitoring System
- EMSA – Electromagnetic Signature Analysis
- MCSA – Motor Current Signature Analysis
- IR – Infrared Thermal Cameras

Limitations of Potential New Technology

- Data, Data, Data
 - Security control for third party access. Ownership of data?
 - Data “pipeline” constraints.
 - Streaming vs batch.
 - How do we assemble it?
 - How do we move it?
 - Where do we keep it?
 - How long do we keep it?
 - How much and what type to do we keep?
- My goal is to build a universal “Ethernet Port” or data pipe at Duke so third parties can securely access our data.

Potential USEA Partnership

- Participate in I4Gen?
- Existing Data Sources/Simulator to provide data?
- Digital Twin to generate data?
- Navy Project - SBIR Phase I Topic A18-034 *Machine Learning Enabled Near-Real-Time Situational Response for Mechanical Systems*
- *Research on FMEA using MCSA or EMSA data*