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Continuous Online Monitoring for Process Anomaly Detection and Predictive Maintenance

Plant Modernization Pathway Stakeholder Engagement Meeting





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TALEN
ENERGY

Xcel Energy

PSEG

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VICTRA
ENERGY





Process Anomaly Detection

- Operates with unlabeled data, making it ideal for systems and components with limited failure history
- Effective in detecting general equipment failures by recognizing changes in plant physics and correlations
- Highly adaptable, can be deployed across diverse systems due to its reliance on data patterns rather than predefined labels

Predictive Maintenance

- Operates with labeled data and work order information, providing increased sensitivity and diagnosability for known failure modes
- Targets specific equipment that undergoes routine preventative maintenance, enabling the transition to predictive maintenance reducing maintenance costs
- Enhances reliability by anticipating failures before they occur, allowing for condition-based intervention



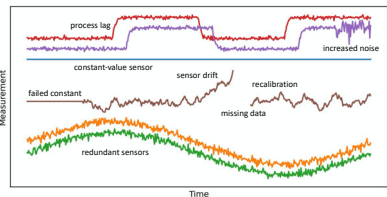
Process Anomaly Detection

- Current approaches to anomaly detection:
 - Perform some preprocessing
 - Use groups generated manually from subject matter experts (SMEs)
 - Focus on high-value systems
 - Require selection of normal and anomalous periods during training
- INL's Automated Latent Anomaly Recognition Method (ALARM) suite of tools can:
 - With minimal effort, model a large percentage of a given plant, including numerous systems that are typically overlooked for modeling
 - Be adapted to new NPPs with minimal involvement from subject matter experts

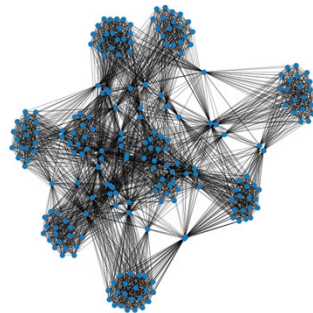
The ALARM toolbox contains a suite of algorithms and tools for automated and equipment-agnostic anomaly detection

Training – INL

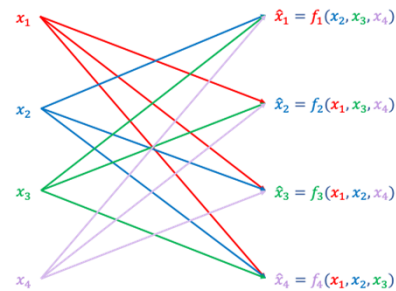
Deployment – USA



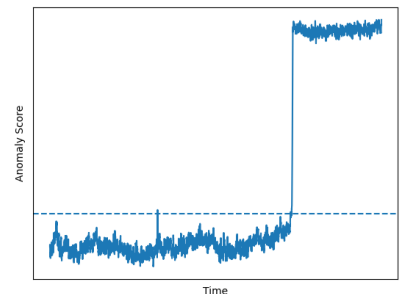
Preprocessing



Grouping



Modeling

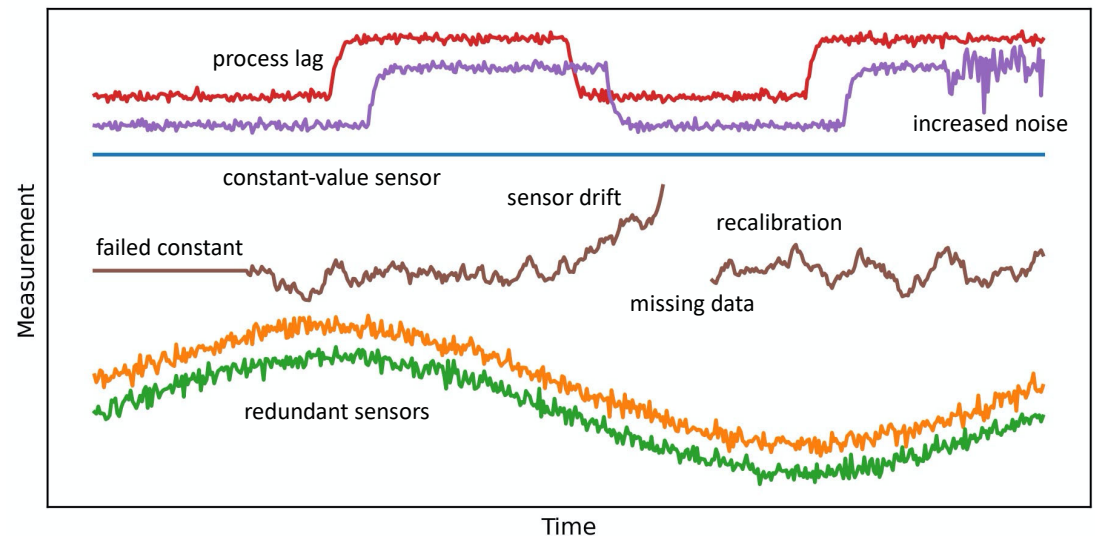


Monitoring

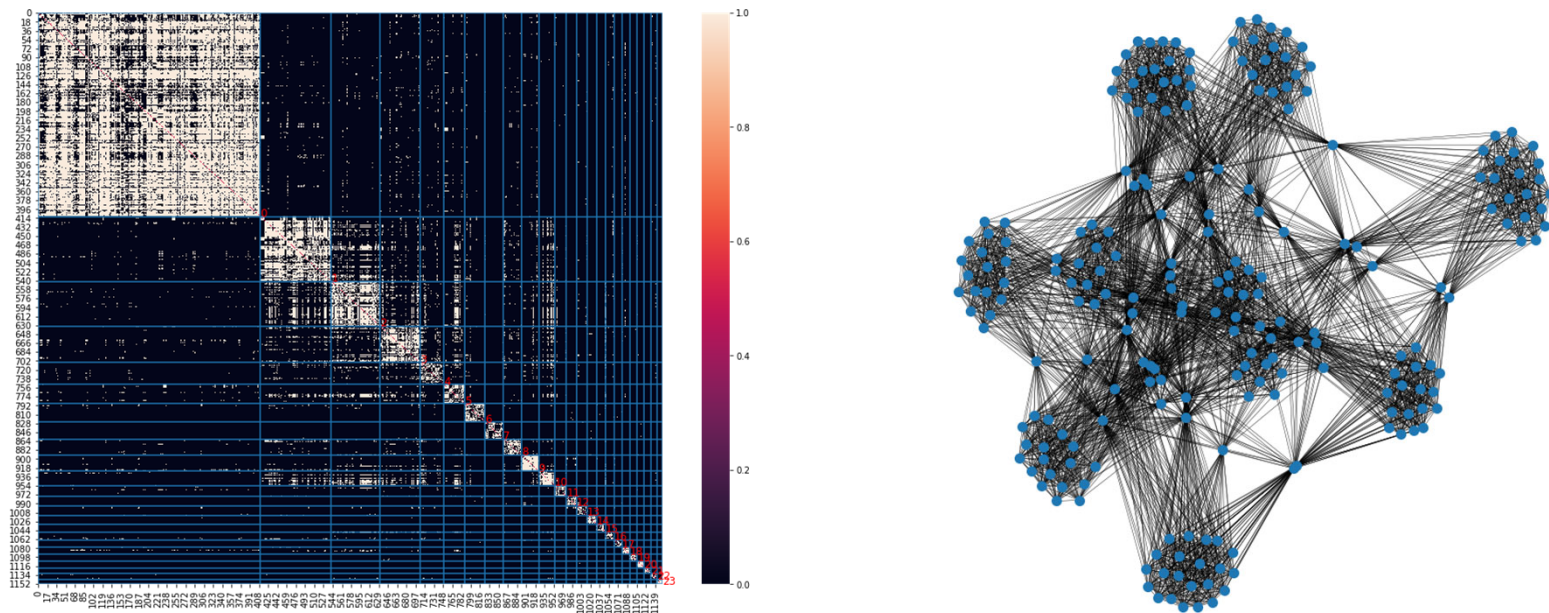
To minimize performance issues caused by inconsistent data, automated preprocessing was used to address a range of issues seen in the provided data

The preprocessing steps included:

- Unifying sampling intervals
- Separating numeric/categoric data
- Handling unusual sensor patterns
- Identifying redundant sensors
- Accounting for process lag
- Normalizing sensor scales
- Removing outlier data
- Detecting failed-constant data
- Accounting for missing data



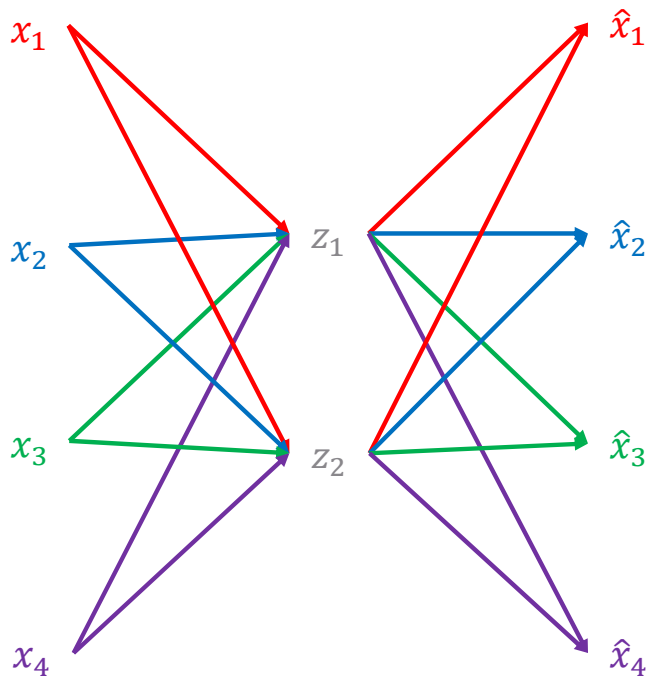
Due to strong correlations across different subsystems, the grouping process used a multivariate correlation approach that allowed for overlapping groups



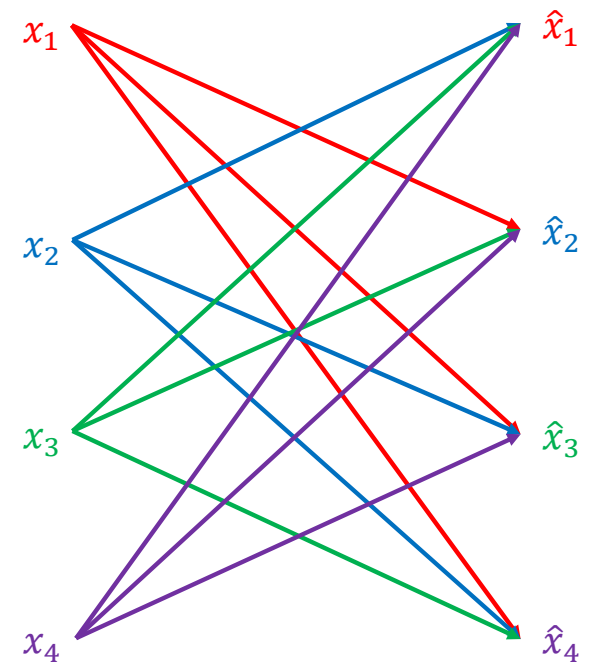
The grouping methods implemented on NPP data generated over 1,000 groups and monitored more than 1,500 unique sensors

For detection, the PCA and INL-developed LOVO models were used, which calculate anomaly scores as a function of prediction error

Principal Component Analysis (PCA)



Leave-One-Variable-Out (LOVO)

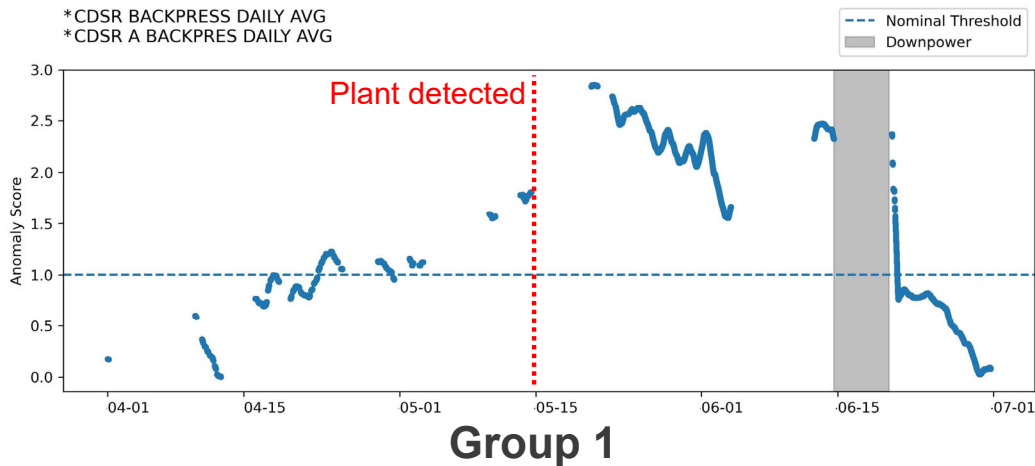




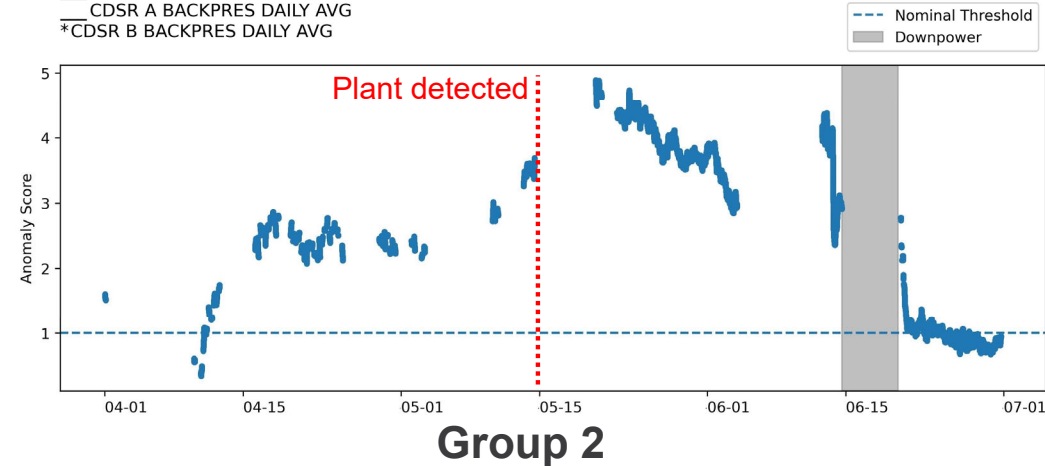
Using NPP data, the algorithms generated four groups (two shown) that detected a condenser anomaly without prior knowledge of its type or location

Expected behavior: scores rise in response to a developing problem and decrease once the issue is resolved through maintenance

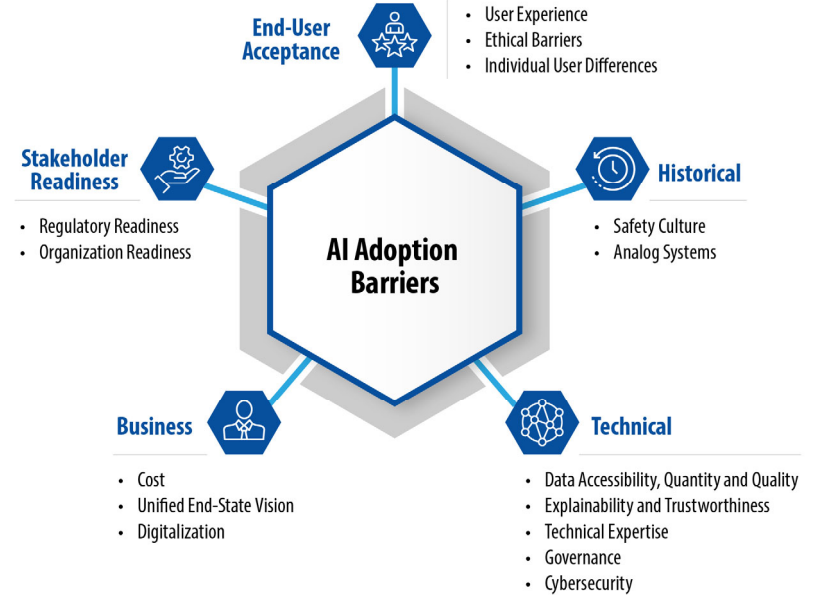
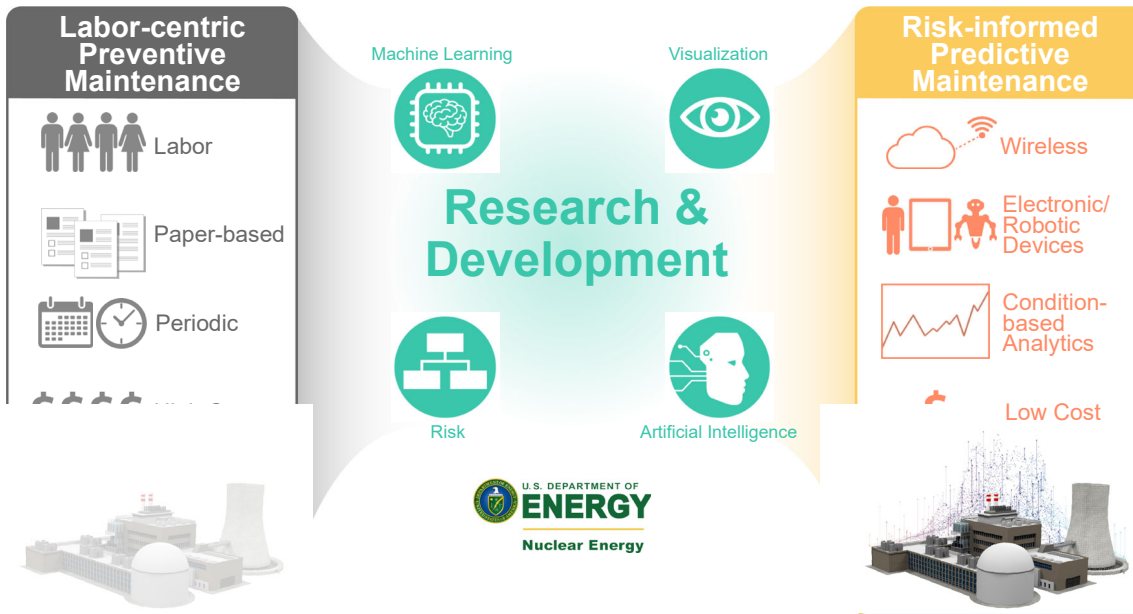
*CDSR BACKPRESS DAILY AVG
*CDSR A BACKPRES DAILY AVG



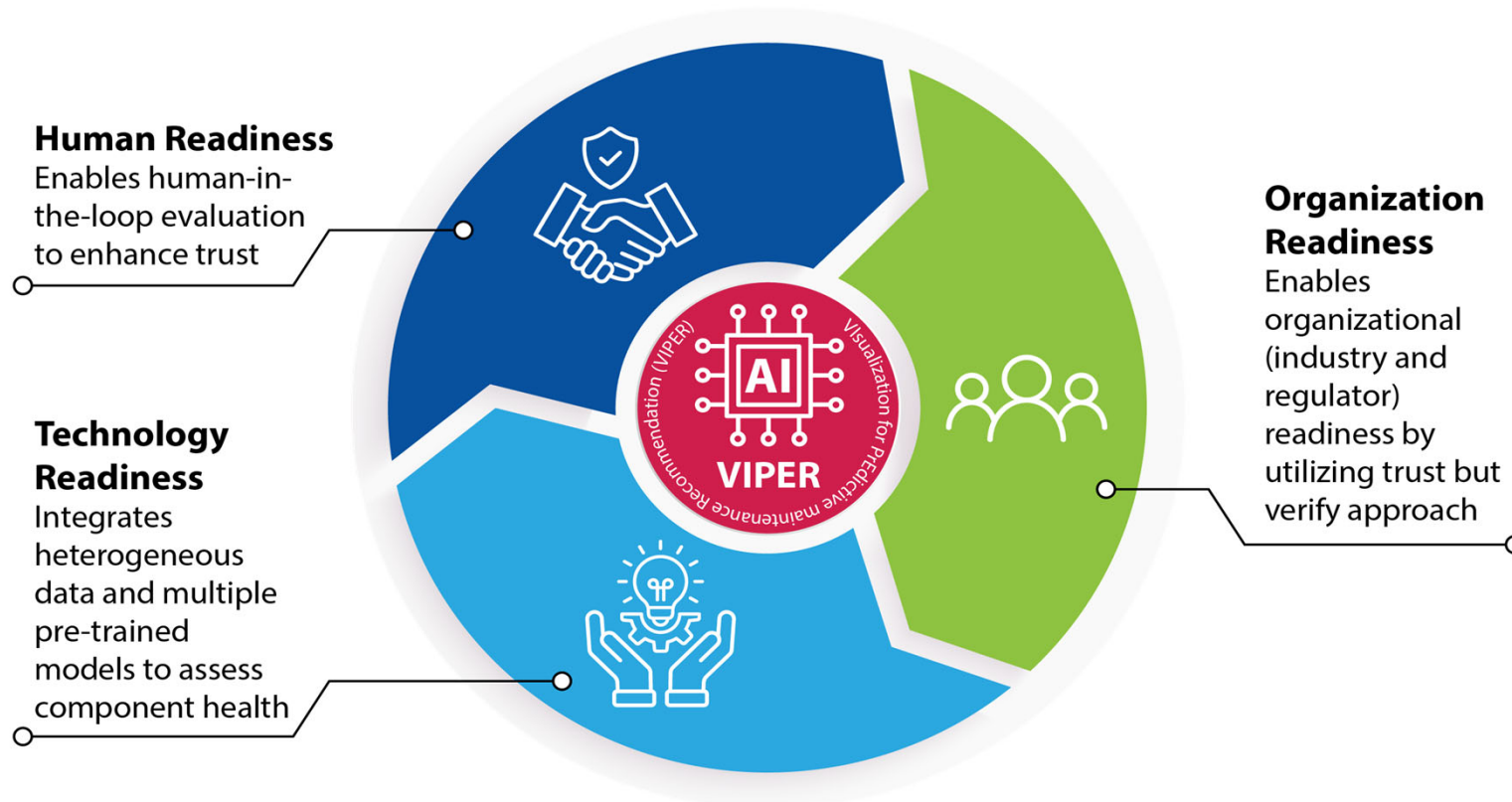
* PRZR PRT T
* CNTMT AIR TEMP ELEV-697
* CNTMT AIR TEMP ELEV-738
* CNTMT AIR TEMP ELEV-755
* FCU 12 MTR STR T
* FCU 14 MTR STR T
*Redundant Group:
— SAS CNTMT TEMP HI ALM LIM
— SAS CNTMT TEMP AVG 15MAVG
*Redundant Group:
— CDSR BACKPRESS DAILY AVG
— CDSR A BACKPRES DAILY AVG
*CDSR B BACKPRES DAILY AVG



Predictive Maintenance



Visualization for PrEdictive maintenance Recommendation (VIPER)



VIPER Interface

For Research Purposes Only

Diagnosics Trends Help

Which Dataset to use: Data4

Type of Diagnostic Model: RF

Compare or Explain: Compare

Which Explanation Model: SHAP

Which Variable to Investigate: DT

Quit Reset

DT
 MOB_Temp
 MIB_Temp
 Motor_Stator_Temp
 Motor_Current
 Threshold

Variable	Value	Unit
1 DT	16.557	F
2 Motor Current	242.29	Amps
3 MOB Temp	107.41	F
4 MIB Temp	107.77	F
5 Stator Temp	141.55	F
6 Gross Load	TODO	MW

ML Output	Diagnosis	Confidence
1 Diagnosis	CWP Diffuser	100.0%
2 Inlier	Yes	N/A

Zoom In Zoom Out

ARIMA prediction for DT [S1.T0487A] - [S1.T0486A]

Parameter

Time (hrs)

Comparing Multiple Variables

Parameter

Time (hrs)

Density Estimate

Historical context for DT [S1.T0487A] - [S1.T0486A]

Density Estimate

Variable Value

Diagnostics Trends Help

Which Dataset to use

Data1

Type of Diagnostic Model

RF

Compare or Explain

Compare

Which Explanation Model

LIME

Which Variable to Investigate

DT

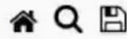
Quit

Reset

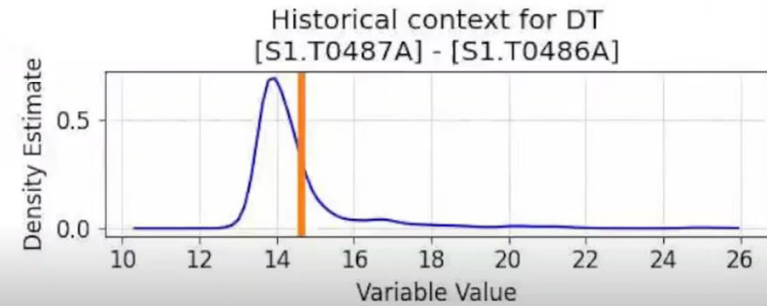
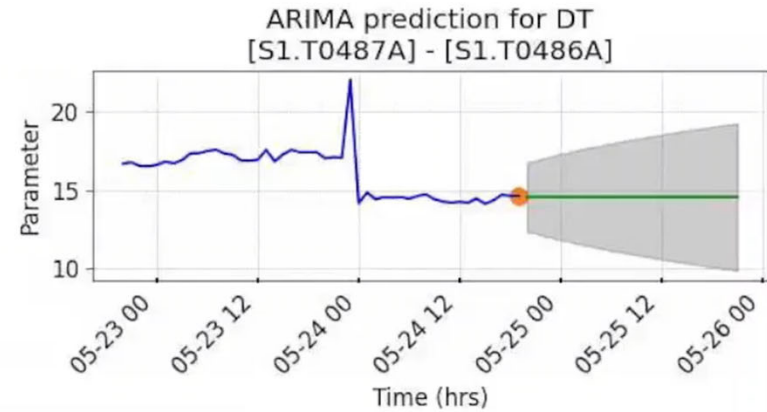
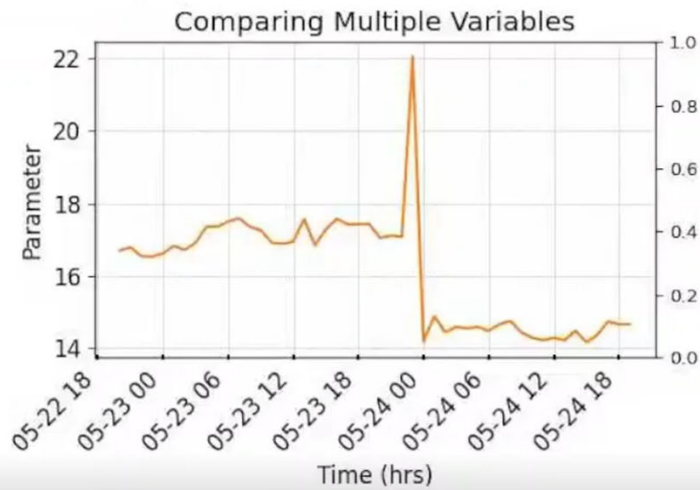
- DT
- MOB_Temp
- MIB_Temp
- Motor_Stator_Temp
- Motor_Current
- Threshold

Variable	Value	Unit
1 DT	14.648	F
2 Motor Current	260.15	Amps
3 MOB Temp	104.13	F
4 MIB Temp	72.362	F
5 Stator Temp	173.80	F
6 Gross Load	1225.2	MW

ML Output	Diagnosis	Confidence
1 Diagnosis	Healthy	79.9%
2 Inlier	Yes	N/A



Zoom In Zoom Out



Diagnostics Trends Help

Which Feature to Explain?

Select Here

I am a chatbot, how can I help you?

reference_data/data.json

Load Reference DB

image_data/scalable/FigureA-1_caption.PNG

Load Image

please enter a path to database

please enter a path to an image

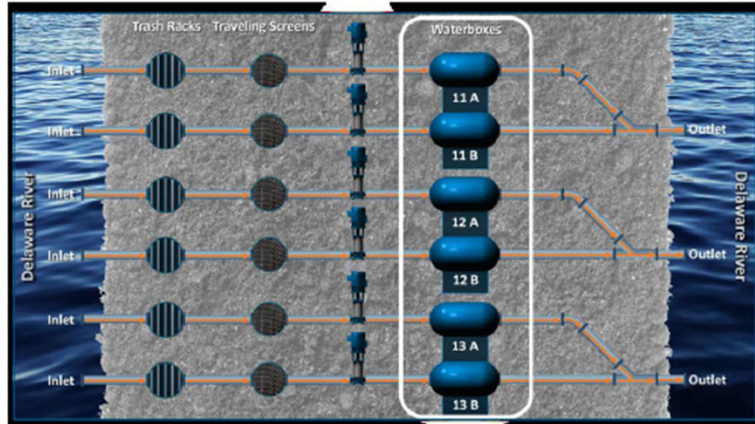


Figure A-1. Salem Unit 1 CWS with main condenser consisting of three pairs of condensers.

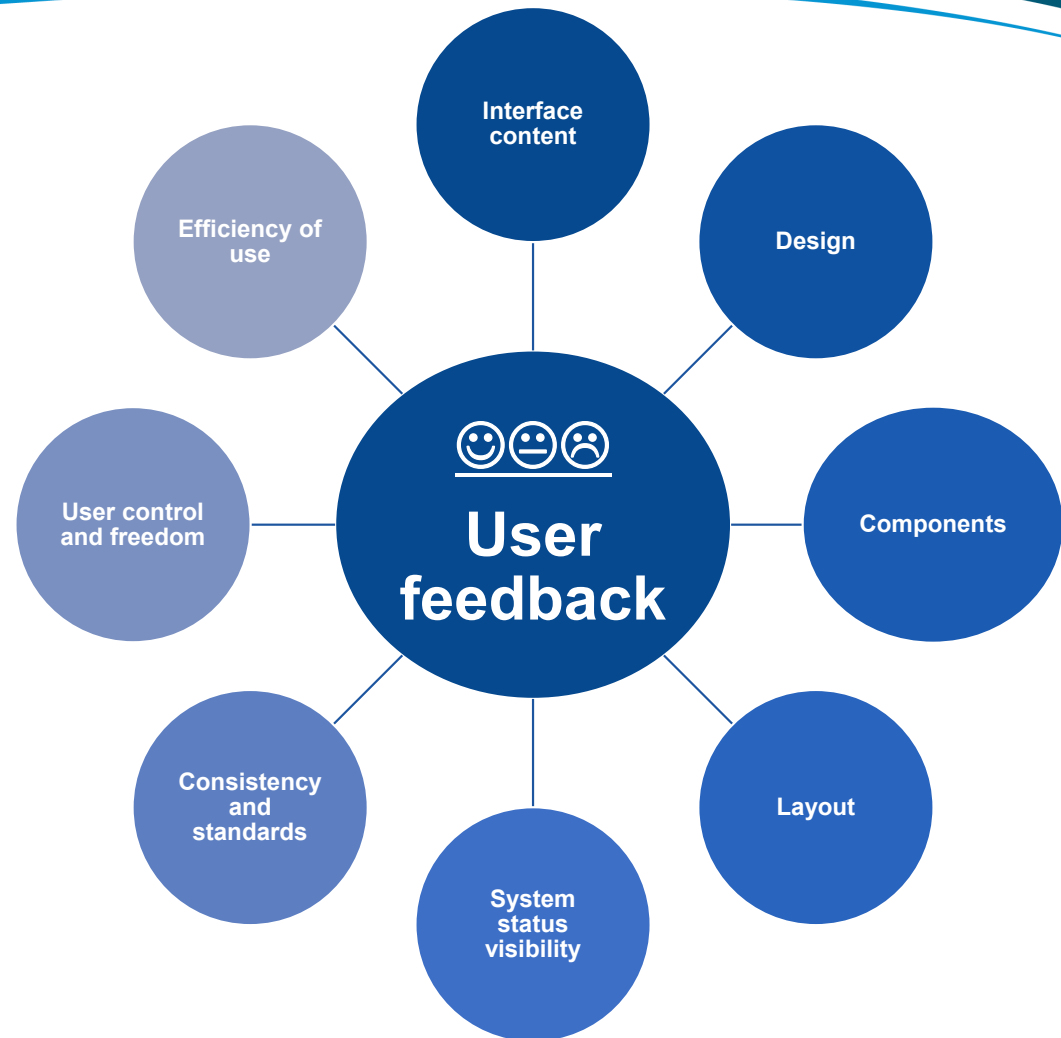
Select an option.

Clear Conversations

Send

Human Factors Evaluation

- Human Factors scientific expertise essential ingredient to AI success in nuclear
- Two complementary studies evaluated usability
- Quantitative and qualitative data collection
- Multi-generational testing
 - plant personnel and new generation engineers
- User feedback essential for AI adoption and HTO readiness



Human Factors Key Findings

VIPER technology favorably received

- Plant personnel:
 - requests to include desired status for comparison
 - no unnecessary info on display
 - “trust” an important research topic
 - important implications for psychology safety
- New generation engineers:
 - indicated diagnosis was clear
 - requests to improve checkboxes
 - described interface as relatively easy to use (low effort required)
 - high information situation awareness



Both populations indicated desire for a layered architecture display with z-axis (i.e., simplified interface)



Conclusions

- INL's ALARM and VIPER toolsets offer two complementary paths to improving plant operations and maintenance
- Using ALARM, models can, with minimal effort, be used to monitor a large percentage of a given plant, including numerous systems that are typically overlooked for modeling
- With VIPER, plants can transition their maintenance strategy for critical equipment from preventative maintenance to predictive maintenance, providing explainable insights to support operations
- Implementation of these methods represents a significant advancement in automating operations and maintenance activities in NPPs, promising enhanced efficiency, reduced costs, and improved safety through early anomaly detection and data-driven maintenance



Sustaining National Nuclear Assets

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