Equipment Anomaly Detection

Detect, Evaluate, and Disposition Potential Equipment Anomalies

About Curtiss-Wright

Curtiss-Wright offers a comprehensive range of products and services that support commercial nuclear power plants.

Our advanced technologies and innovative solutions have been used in civilian operating nuclear power plants for over 65 years, sustaining the safe and reliable operation of these plants throughout the world. We continuously provide technologies and experience in support of aging equipment management/replacement, as well as offer proactive solutions to critical plant issues.

Equipment Anomaly Detection (EAD) is a neural network artificial intelligence-based application for detecting equipment anomalies. EAD automatically learns relationships between hundreds of equipment parameters.

EAD models are easily updated as new normal operating conditions are encountered and can provide contextual data for easy action planning or other disposition. EAD is an ideal option in many operational conditions such as model training, general day-to-day use by system engineers, and when limited domain expertise is available for initial model build.

The EAD system will:

- Help identify early indications of equipment failures
- Improve equipment reliability
- Allow preventative actions to mitigate failure
- Detect anomalies and deviations from the standard operating parameters of the equipment
- Indicate the beginning of an equipment failure
- Monitor fast transient behavior like startups, shutdowns, and rapid operating changes

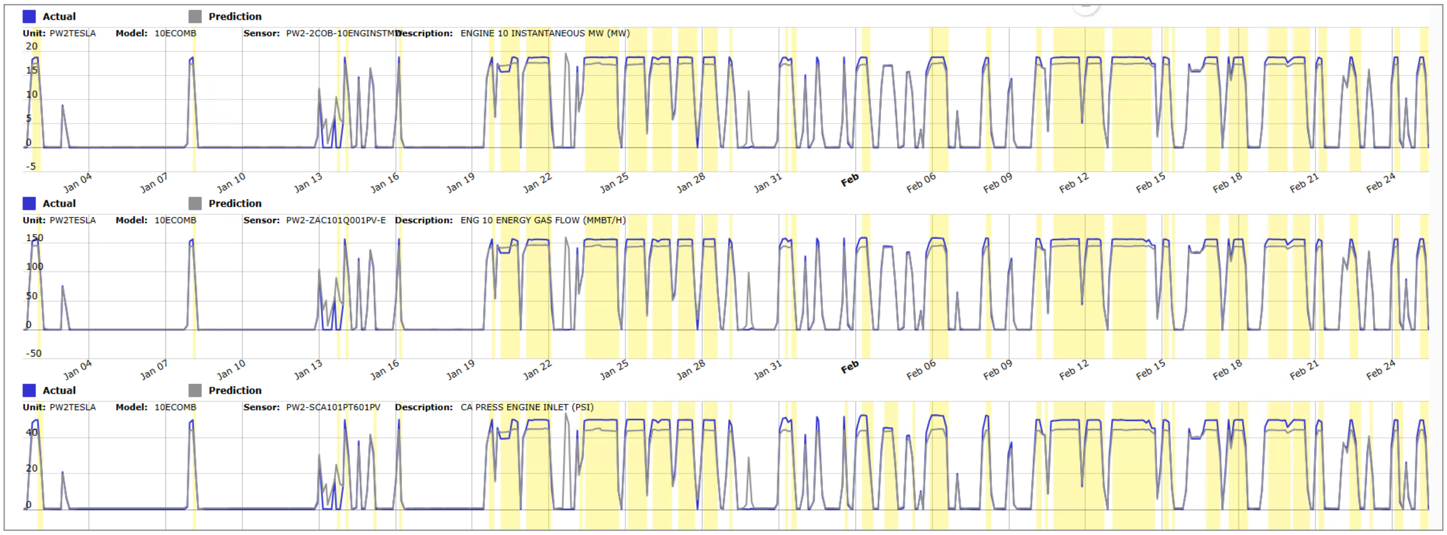

Figure 1: Sample EAD Trend

How does EAD Work?

EAD uses a specific type of artificial recurrent neural network (RNN) architecture composed of long short-term memory (LSTM) autoencoder units. This architecture has demonstrated success in producing expected values for its collection of modeled sensors based not only on the current dataset, but also upon the data from a configured number of time steps into the past.

As such, EAD can effectively monitor transient behavior like startups, shutdowns, and rapid operating changes that are more challenging for similarity-based models like FAMOS PdP.

In addition, RNNs can evaluate large numbers of sensors, including vast combinations of digital inputs. Combined, these features provide anomaly detection functionality that is sensitive to degradation with fewer false-positive indications.

EAD models are constructed and trained with historical data using the same Windows-based client as FAMOS PdP—the EAD Architect.

Trained models are deployed to the EAD server to produce runtime predictions.

Real-time alarms and trending features are provided to end users on the integrated EAD web-based graphic user interface (GUI).

Using historical data, EAD can produce robust, efficient models that can be trained with little involvement from subject matter experts, yet still provide early warning of equipment failures with fewer nuisance alarms. EAD also includes alarm functionality based on the deviation of individual sensor behaviors from predicted values (or residual) for any given snapshot of data.