Harnessing data fusion to optimize stressed power plant performance

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Big Data holds the potential to provide owner operators predictive operating models to optimize efficiency, reliability and life of gas turbine generation assets operating in response to renewable energy grid requirements.

Today's accelerating drive toward reduced carbon emissions, and the operational demand of changing duty cycles on power generating assets, come at the expense of reduced performance and increased maintenance requirements under operating conditions that accelerate wear and tear and consume component life at a faster rate.

Given the increasing focus on operating flexibility, from rapid start-stop cycles and almost instant loading to fill the generating gaps associated with intermittent renewable energy systems, the impact on equipment life (systems and components) poses a formidable challenge.

Changes in plant operating environment as dictated by shifting market demand has created a real-time need for information not foreseen when the current fleet of gas turbine plants was designed. Data and knowledge relevant to equipment condition has become of first order value to the owner operators confronted by these challenging operating scenarios.

This all points to the need for enhanced operator decision-making capability to anticipate equipment issues before they happen and allow time for preventive measures to avoid downtime and keep plants in a ready-to-run condition.

Data Fusion offers that capability. Time-series operating data and physics-based models combined with near real-time data and analytics hold the key to improving predictive capability.

Armed with this predictability, power plant operators can be better informed, reduce disruptions and increase productive service hours. Key is the ability to transfer learning and experiences, on an anonymized fleet basis, from one plant operator to another.

This enables operators who have not yet experienced emerging field problems and issues to learn from those who have. Mitigation and planning steps may then be taken earlier to avoid costly and disruptive forced outages.

Data Fusion research team

To meet the Data Fusion challenge a team of specialists was assembled comprising researchers from Strategic Power Systems (SPS), Turbine Logic, and two U.S. Department of Energy labs, the National Energy Technology Laboratory (NETL) and Oak Ridge National Laboratory (ORNL).

The team collaborated throughout 2019 and 2020, supported by DOE's Fossil Energy and Carbon Management Program through its High-Performance Computing for Materials Program, which provided access to high-performance computing facilities at both national laboratories.

Each team member brought unique skills, strengths and capabilities to the table (Figure 1). On the industry side, SPS represented the concerns and challenges faced by plant operators and provided supporting data, while Turbine Logic provided project management and technical oversight.

ORNL was responsible for machine learning models capable of detecting real time and long-term anomalies which could lead to reduced reliability, while NETL delivered physics-based remaining life prediction models with focus on the power plant's critical bottoming cycle components.

All team members worked toward the common program goal: *improved, self-learning power plant life consumption models for use by power plant operators, made possible by Data Fusion*.

ORNL Contributions

The researchers at ORNL focused their efforts on experience field data using a commercial product developed by SPS called the Operational Reliability Analysis Program (ORAP).

ORAP tracks plant operational, performance and event data to benchmark reliability, availability and maintainability (RAM). Specifically, the dataset encompasses unit pedigree data, event data (for instance, failures, scheduled and unscheduled maintenance, etc.), operation profile data and age data.

Since the available dataset covers several power plant units in various operational conditions, it provides valuable insight for understanding power plant operational anomalies and correlations with changing operating conditions.

The ORNL team used this RAM data to develop machine learning models that can predict the time to next failure and forecast failure trends, which are useful for optimizing power plant operation strategies.

Multiple machine learning models were trained to predict the likely time of the next forced outage. Model accuracy was evaluated against over 10 years of historical data.

AI auto-learning a key

Key to this work are artificial intelligence (AI) auto-learning techniques that require no additional input or training by the power plant operator and end user. Typically, many AI techniques employed by power plants for diagnostics require constant monitoring by an engineer and often must be retrained manually.

This project was designed from the outset to work with automated learning and updating so plant engineers can spend their time using the results, rather than having to tinker with models.

Two types of AI models were prototyped. The first explores long term changes in Reliability, Availability, and Maintainability (RAM) as it relates to power plant operational characteristics.

These characteristics include the plant's hardware pedigree and its operating duty-cycle characteristics, such as starts, fired service hours,, and other metrics which describe how a plant is operated.

The RAM AI model then uses detailed event histories for the comparable fleet of plants, or peers, to build a predictive model indicating the frequency of failure and forecasts the next likely event. This proof of concept allowed exploration of model use with power plant operators in mind.

While the OEMs of major plant equipment normally provide standard data on the ordinary lifetime and maintenance cycle of a unit, the actual RAM performance for a specific unit in the field, whether better or worse, depends on how the unit has been operated.

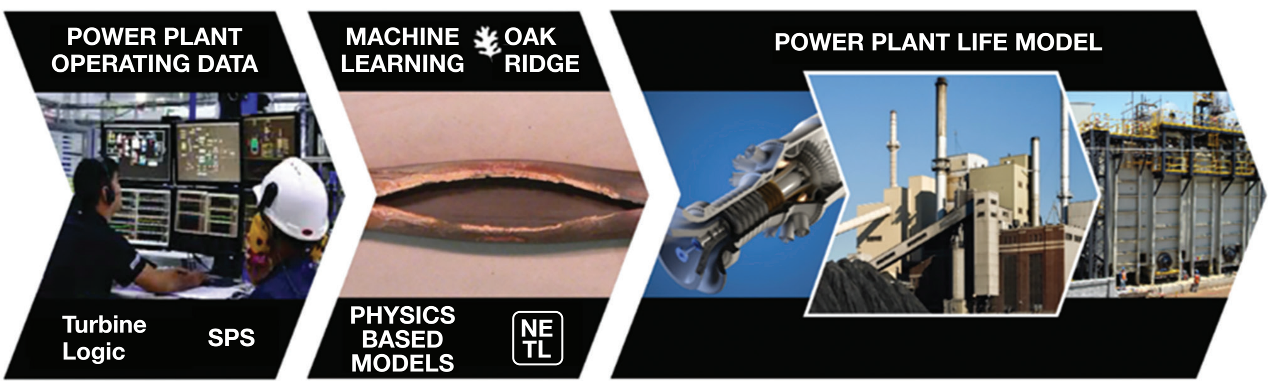
In ORNL's testing scenarios, the machine learning model was used to quantify the risk of the next failure by estimating the expected "increased age value".. Figure 2 provides an example of predicting when the next forced outage will occur based on historical and projected starts and fired hours.

The green lines show historical information and the cumulative number of forced outages. Operating history at this plant shows a long period of good reliability followed by a steep increase in forced downtime. The blue lines show the actual subsequent events experienced at the plant, while the red lines show the AI model forecasting.

The model uses failure data from the specific plant's history and from all other comparable peers to build a prediction. This means that even if this plant has not yet experienced a forced outage event, emerging issues in peer units will influence the risk profile.

The results track well. Statistical testing showed the model to be reasonably accurate at predicting the next forced

Figure 1. Predictive data fusion models. Collaborative industry and government research team is working on operational self-learning models that will enable operators to predict remaining power plant component life, anticipate forced outages, reduce downtime.



event, with the goal being to determine statistical confidence.

Further work is ongoing at ORNL to further refine accuracy and enable a confidence interval on the prediction to better give operators a sense of model accuracy.

Establishing early warning system

Besides using machine learning for long-term reliability prediction and projection of the next failure, the ORNL researchers used near real-time data to determine the feasibility of forecasting fine-grained detail of power plant operations several minutes in advance, establishing an early warning system for plant operators.

Such a system is not intended to replace traditional M&D monitoring, but would correlate abnormal instrumentation readings with the long term RAM reliability models just discussed. A side benefit is that observed anomalies can be reported and issues that might otherwise lead to unexpected failures and forced outages could be addressed and mitigated.

To achieve these outcomes, ORNL leveraged convolutional neural networks to learn from historical sensor data and make predictions about the future state of power systems.

While the math is somewhat involved, the networks learn the complex relationships between the hundreds of sensors feeding data from the plant on a 1-second sample interval.

Unlike traditional AI systems, which work with continuous process data and must be manually retrained, this model learns continuously with no manual retraining. ORNL also built a system for visualizing predictions (second by second) from a vast array of sensors to better understand the efficacy of the neural network making predictions.

See Figure 3 as an example for predicting generator load failures. The x-axis shows the time of day and several days of plotted data. Green shows data used to provide an initial training for the model (6 days' worth). The blue line then shows a day used for prediction where the model prediction is overlaid in orange.

The AI model continuously learns using 5 minutes of past data to predict 30 seconds into the future. The difference between the actual signal and the model's 30 second ahead prediction can detect anomalies.

These can be used with the data fusion from other peers to detect trends and correlate to potential failure modes. In the end – it all serves to better inform operators of potential emerging issues with adequate time to take preventive measures.

NETL Contributions

The NETL effort is focused on creating physics-based models for optimizing power plant operation to reduce failures during cyclic operation. Particular focus of this effort is being placed on issues related to the thermal cycling of critical HRSG superheater and reheater tubing.

The lab's JOULE 2.0 supercomputer and commercial Ansys engineering simulation software (along with an assortment of modules) were used to simulate various realistic operating scenarios and to resolve issues created by the combined effects of fluid dynamics, thermal stress, heat transfer and structural mechanics on plant materials and components..

Fed with this data, the models enabled predictions of local stress profiles on components in terms of thermal cy-

Figure 2. Age-based machine learning models. Developed by ORNL to quantify the risk of next forced outage based on accumulated number of start cycles and fired hours of operation.

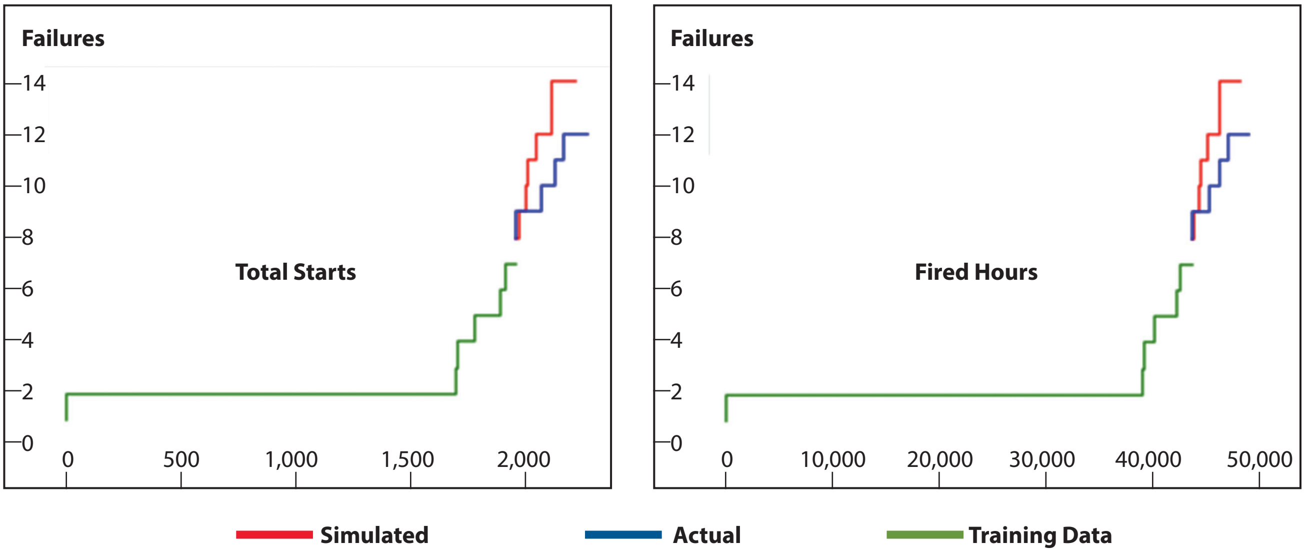
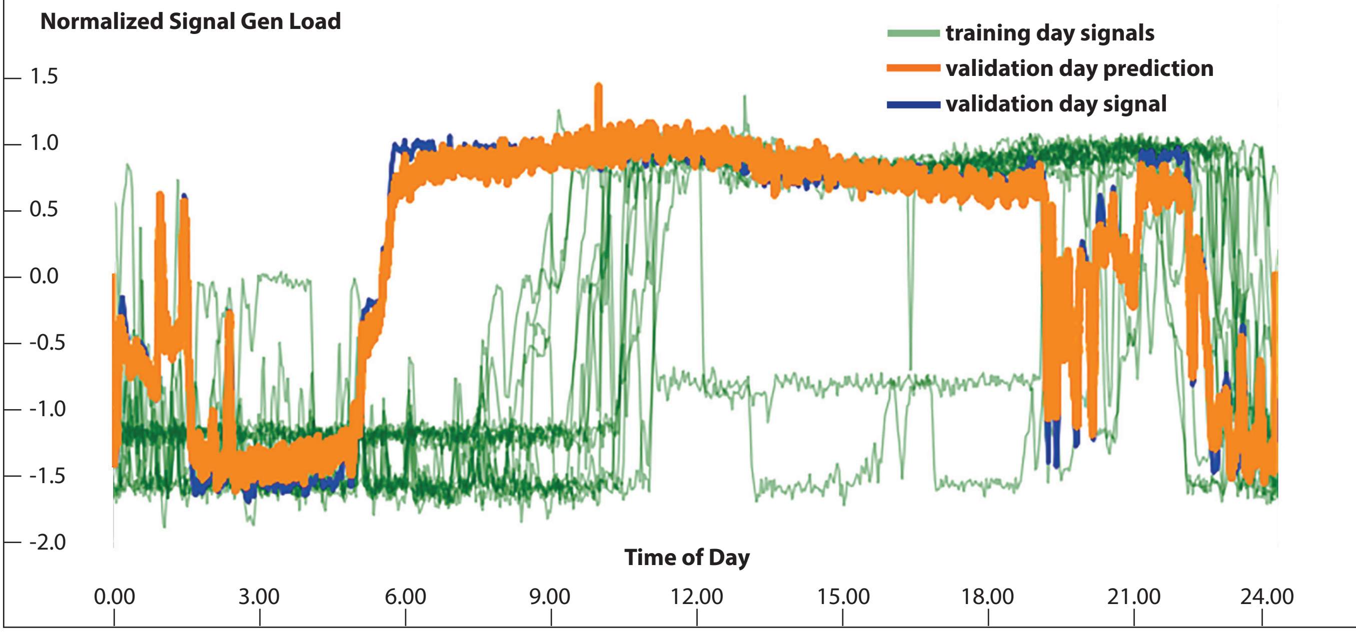


Figure 3. Plant's overall load on several days. ORNL researchers used neural networks to predict power plant operation, Sensor data for several days shown by green lines were used to train model. The validation day's signal is shown in blue, with the predicted signal in orange closely matching the observed signal.



cles. Fluid flow and material stress analysis were also incorporated to model component performance while simulating different scenarios to solve for combinational effects.

Improving prediction of cyclic life

This contributed to better predicting the impact of cyclic operation on superheater and reheater tube durability. When coupled with real time data from the models (discussed earlier), this could enable early warnings of potential tube cracks and leaks.

The opportunity to add additional instrumentation or sensor capability in the reheater tube area will be assessed during the second phase of the project. This would provide invaluable process data for predictive purposes.

The NETL researchers used near real-time process data characterizing the operating environment and dynamic conditions, from start-up to shut down, which affect heat recovery steam generator (HRSG) tube life.

Datasets from all natural-gas combined cycle (NGCC) and coal-fired power plants reporting to ORAP (historical and current data)were analyzed to categorize operating conditions and reported failures to identify specific areas of focus for the modeling.

The NETL team also set up analytic models to predict the temperature/pressure distribution within both flue-gas and steam-side flow paths and in fin-and-tube materials for material fatigue and component life analyses.

With these computational tools, NETL simulated equivalent stress profile, over time, for hot, cold and warm plant starts. This was then used to demonstrate the ability to calculate the impact of thermal cycling on remaining life (cycles) for a sample superheated steam reheater tube.

Follow-up efforts at NETL will focus on unifying the physics-based models and creating associated neural network models with the historical data available from ORAP, along with the near real-time process data, to further enhance the tools for prediction of remaining tube life..

Work Going Forward

The Data Fusion team's continuing work to realize data-fused plants is already underway. The next step involves integrating ORNL's machine learning to test live data on long-term RAM prediction, short-term fault detection and interaction effects between these two approaches in the real-world, while validating NETL physics-based models.

This follow-on activity is focused on extending the research beyond proof-of-concept phase (Figure 4) with the support and collaboration from operating power plants; the project focus is Data, Modeling, Prediction, Validation, and Deployment.

A Synthetic Weibull process will be developed combining actual events from ORAP Data with predicted data (synthetic events) to generate life parameters. These parameters will be used in simulation to support the owner/operators by providing information on failures for planning and corrective action to reduce the impact of unforeseen downtime.

As reported by Strategic Power Systems CEO Sal Della Villa, significant steps forward have been made in realizing the concept of 'smart power plants' that use life predictive concepts and analytics on-site, as opposed to traditional remote monitoring.

"We're looking at actual tangible benefits that can be deployed in the very near future and even change what it means to work in an American power plant. This is just one example of what can happen when the multifaceted capabilities of DOE's national labs and our country's power sector come together.

"The problems we face in meeting growing energy needs and addressing climate change are immense, but there's nothing we can't overcome by bringing together actual operators and the brightest minds in R&D."

The results will also enhance the eXtremeMAT (XMAT) National Laboratory Consortium program to accelerate the development of alloy materials that can withstand high temperatures and pressures.

Such alloys are necessary to refit the existing power plant fleet and construct new plants designed for cyclical rather than continuous operations which induce immense strain on the facility components.

With the right application of data science, the time and costs for alloy development and lifetime prediction modeling can be reduced. This makes these tools more economical and attractive for private investment, accelerating the adoption of new technologies on a large commercial scale to address climate change while keeping the electrical grid stable.

The value of this work goes far beyond SPS, Turbine Logic, ORNL and NETL. The results of their work can inform other DOE sponsored activities, adding benefits and value beyond any one project to ensure that valuable data during this process informs technology development in a challenging and dynamic energy market nationwide and throughout the world.

Such collaboration in the common interest will only become more important during the coming decades as more nations continue to industrialize to meet the needs of their people and improve their quality of life.

Just as many conveniences of modern life would not be possible without Big Data, such as the way people communicate, travel, shop and work, so too can Big Data pave the way for solving the greatest energy and environmental challenges of this century. ■

Figure 4, Project team's work going forward. Focus is on extending research beyond proof--of-concept phase with collaboration of operating power plants.