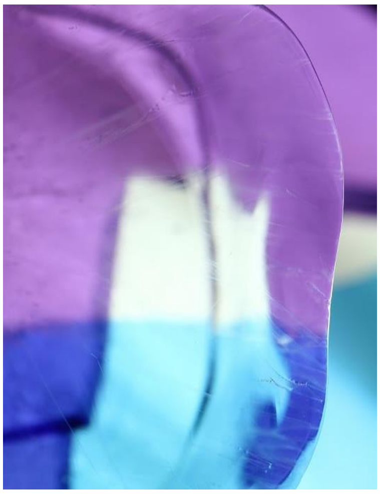
Challenges and Success in the Implementation of a Fleet Wide PHM for Energy Applications



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***Abstract*— Energy industry companies, both OEMS and operators, are quickly adopting fleetwide asset monitoring strategies in an effort to improve reliability and increase revenue. To derive efficient business insight and value from monitored equipment, seamless end-to-end solutions are needed - from the sensors to IT infrastructures. And, advanced tools and techniques are required for data transfer, management, and analytics. Further, systems management is needed for the many sensor connected data acquisition systems nodes. This paper details challenges and sample solutions in the design and integration of PHM Systems in the energy industry.**

Keywords- Anomaly Detection; Big Data; Data Management; Data Source Management; Diagnostic Visualization; Feature Extraction; Predictive Analytics; Predictive Maintenance; Sensor Selection

I. INTRODUCTION

The power generation industry is undergoing a transition from traditional power using Nuclear and Coal to more efficient gas turbine combined cycle technologies. While many of the traditional power plants have been in existence for many years, they are aging and require more maintenance [1]. Further, the cost of coal and nuclear fuel has increased significantly in the past several years. While natural gas is cost competitive in comparison to coal and nuclear fuels, the gas turbine combined cycle technology is more complex, and often more costly to repair. As a result of older power plants aging, and newer plants being more complex, a growing need for fleet health monitoring coupled with automated diagnostics and prognostics is needed.

In order to meet these needs, the power generation industry continues to identify and deploy new technologies for fleetwide monitoring. These technologies include information technologies such as data storage and management, expanding sensory data sources, automated sensory data recordings, and improved automation in analysis of sensory data.

II. POWER GENERATION INDUSTRY CHALLENGES

A. *Aging and New Power Plants*

The United States Power Industry has relied on Nuclear and Coal based power generation for the majority of base load demand for many years, Fig 1. As of March 2011, 51% of all generating capacity is over 30 years old.

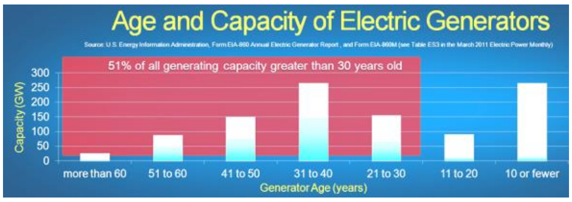

Figure 1. Age and capacity of electric generators

To keep these older generation assets producing power, additional maintenance is required. Adding to the maintenance challenges in power generation, the majority of new assets brought on line in the last 20 years are natural gas based. Combustion turbine and combined cycle power generation plants are more economical to operate, given the lower price in natural gas. However, natural gas plants incorporate newer technology that is more complex and often more costly to repair.

B. *Adding Maintenance Intelligence Information Technology*

To best understand and plan for maintenance requirements in both old and new power plants, additional sensory data acquisition systems are being deployed to improve visibility of rotating and stationary assets. In addition to adding monitoring sensors, information technology is being expanded to detect degradation and predict future performance and maintenance requirements, Fig 3. Research Organizations, such as the Center for Intelligent Maintenance Systems, and equipment vendors are developing information processing technologies to detect degradation and future health of many asset types, including those used in power generation [2].

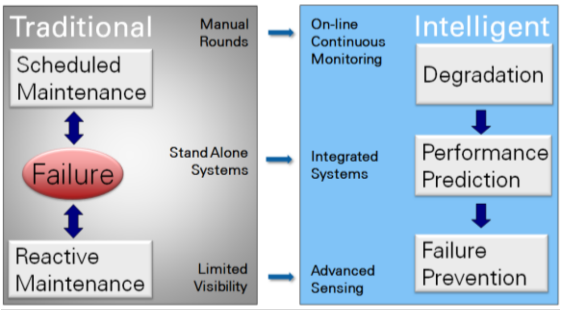

Figure 2. Transformation to intelligent maintenance systems

The transformation from traditional to intelligent maintenance systems requires several key technologies from the information technology domain space. These include embedded signal processing in the sensory data acquisition systems, systems management, data management to store and access the massive amount of new sensory data, and of course improved algorithms to process the new sensory data.

III. Duke Energy Business Drivers

A. Duke Energy, the Largest Regulated Power Producer

Duke Energy (Duke) is the largest power generation holding company in the United States. It operates a mixed portfolio of generation, totaling 58GW with 41GW non-nuclear [3]. The power generation assets are distributed amongst 81 plants, with some additional overseas holdings. When looking at the distribution non-nuclear (fossil) technologies used to produce power, 50% is coal, 40% is combustion turbines and combined cycle. Most of the plants are located in South Eastern United States with some in the Ohio valley.

Duke's traditional equipment condition monitoring has target goals of operating within design limits, identification of and planning resources for maintenance needs, with measurable reduction in outage time and increased availability. Maintenance technicians have historically used manual technologies, with sensory data collection conducted only during physical visits to the machine. Engineering evaluations are historically based on performance and long term trends using a data historian.

In 2010, Duke launched its "SmartGen" program to provide automatic sensory data collection, freeing maintenance personnel to spend time analyzing and reviewing sensory data rather than collecting it. The main objective of the program is to detect operational or equipment problems as soon as possible for the most critical units. This fast identification is expected to yield damage mitigation, shift from forced outages to planned repairs, identification of performance problems, and improved safety all while controlling costs and increasing availability of equipment.

B. Change in Operational Patterns Underscore Reliability

Traditionally, the nuclear and coal fleets provided the baseload of electrical power, running continuously. Duke and other coal fleet operators made large investments to clean emissions. Meanwhile, the smaller coal plants including combine cycle plants and simple combustion turbines were cycled on and off to meet peak demands during the day and summer or winter seasons. This pattern has recently switched, due to the cost of fuel where natural gas prices are low and coal prices are high. Baseload demand is now predominately provided by combined cycle gas turbine and steam turbine operations. Larger coal plants are now used to meet peak demand and smaller coal plants are being decommissioned. The result of this operational change is the combined cycle plants have higher reliability and availability demands. Further, the operating coal plants are experiencing reliability challenges as they operate differently than their design, that is they cycle on and off as compare to continuous operation.

As a result of these increasing reliability demands, the executive team at Duke issued a challenge to leverage new technologies to address increasing reliability demands and workforce optimization. Duke started an internal project in 2010 to explore technology and process changes. It went a step further, to collaborate with the Electrical Power Research Institute (EPRI) to address reliability needs from an industry perspective.

C. Increasing Impact with Industry Collaboration

With EPRI collaboration, technology and business challenge exchanges began to occur across the power generation industry. Exelon, the largest nuclear operator in the United State, meanwhile is experiencing similar challenges [4]. Exelon has limited online vibration monitoring instruments installed, limiting the ability of engineering to identify and diagnose mechanical issues. Plant experts spend too much time manually collecting sensory data, and in many cases equipment is in radiation areas. Exelon's immediate goal is to focus their vibration experts on analysis of equipment as compared to collecting vibration sensory data.

To further collaboration, both EPRI and Duke continue to solicit participation from vendors that provide online monitoring equipment, data analytics, and resource management tools. Fundamentally, EPRI company members are power generation, transmission, and distribution owner operators. Acting as a group, EPRI can help drive standards and invite vendor input on new technologies and best practices.

EPRI for example, hosts both a fleetwide monitoring (FWM) and condition based maintenance (CBM) working group and conference each year. These conferences encourage collaboration with technology and practices exchanges. Both conferences build on the EPRI Equipment Condition Assessment [5] and the Fleet Wide Monitoring for Equipment Condition Assessment [6] reports.

In particular, EPRI and company members are promoting technology innovations in several key areas, Fig 3. These technology innovations range from communication networks, to sensors, to diagnostic / prognostic analytics and data integration / fusion and visualization.

Figure 3. Technology area enhancements

IV. On-line Monitoring Architecture

A. Objectives of the On-line Monitoring System

As stated earlier, the core objectives of an on-line monitoring system are to greatly reduce the time equipment specialists spend collecting the data, and as a result to increase the amount of time specialists spend analyzing sensor data and results from automated analysis, Fig 4. This change from manual sensory data collection is intended to result in improved consistency in diagnostics using automation and standardization. Other improvements include better fusion of technology exam sensory data with process data. The end result is expected to be a more integrated monitoring and diagnostics center with improved visualization, enabling engineering and specialist workforces to perform higher value tasks.

In comparison to manual route based data collection, Fig. 5, on-line monitoring systems overcome several disadvantages. The first disadvantage is sparse data collection schedules. With manual route based exams, specialists visit the machines on schedules perhaps just once per month or once per quarter. These schedules may be interrupted by unplanned higher priority needs of the plant. Duke, for example, makes nearly 60,000 manual exams per month. A second disadvantage is equipment availability for an exam. The equipment may not be in operation during the specialist physical visit. Further, there is a high probability of missing an event, as the symptom of degradation may not adequately show itself during the periodic visit. Fourth, when the technical exam sensor data is collected, it often remains on the specialist's computer, until such time as the specialist determines it is important to report during a face to face meeting. In other words, an individual's limited view of the overall equipment may prevent data from being reported at a face to face meeting. And perhaps most importantly, over 60% of specialist manpower is used to collect sensory data, with limited time left for analyzing and reporting equipment health.

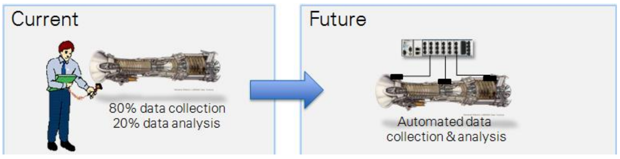

Figure 4. Workforce optimization thru on-line monitoring

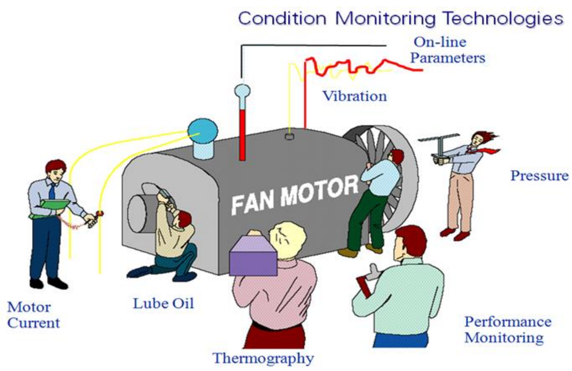

Figure 5. Manual technology exam measurements

B. Architecting the On-line Monitoring System

Over the past several decades, many vendors of data acquisition systems have brought to market and evolved on-line data acquisition systems. Systems have evolved from pure sensory time waveform acquisition and transfer to those with embedded intelligence. Over time, experience has driven embedded intelligence towards data reduction, data quality validation, and data acquisition system health. Further, experience has driven node system management systems that manage configuration and the networks these devices reside on.

To implement an on-line monitoring system at Duke, automatic data collection nodes, capable of measuring sensors from multiple technologies, are added to a computer communications network, Fig. 6. These automated data collection systems are most easily added to the business network, taking advantage of both wired and wireless infrastructures that have appeared in the power generation plants over the last several years. By placing the data acquisition systems on the business computer network, the data acquisition systems avoid interfering with control systems, and face less interference evaluation. A sample data acquisition system, Fig. 7, includes data acquisition hardware, power supplies, fuses, and communication equipment.

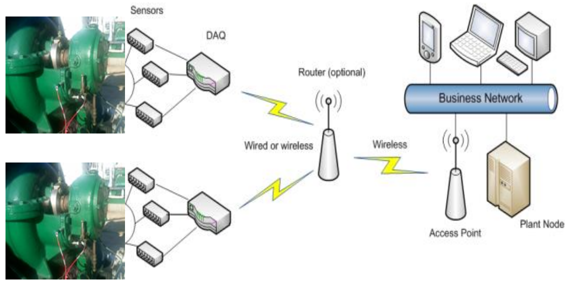

Figure 6. Data acquisition system on the business network

Figure 7. Sample data acquisition hardware cabinet

Data acquisition systems must be able to digitize physical phenomenon from a variety of sensors, both those making dynamic and static measurements. Dynamic measurements are of physical phenomenon that changes rapidly such as vibration, motor currents, and pressure. Static measurements include oil, temperature, flow, and loads. Dynamic measurements may utilize analog to digital sampling rates in the 10's of thousands of measurements per second. These systems are designed to continuously monitor sensors, in order to overcome the problem of missing an equipment degradation indication.

A challenge in continuous monitoring, is managing the large amount of data being acquired. For example, just monitoring two critical feed water pump shafts with two bearings can produce over one terabyte of data per week with continuous sampling. To overcome this sensory data deluge, the continuous monitoring data acquisition systems must be designed to record and transfer sensory data on either a periodic basis or an event bases, Fig. 8.

As a result of the need to reduce the amount of data recorded and transmitted on the network, these networked systems must be both data acquisition and analysis network nodes (DAAN). The DAAN initializes itself on power up and begins monitoring sensory values as digitized by onboard analog to digital converters. Both dynamic and static measurements are made with their time stamps synchronized. Some sensory values may come from communications to local control systems. As the sensory values arrive in memory, the DAAN analyzes the time stamps and values of sensory measurements to determine a periodic trigger, or an event based trigger. With a trigger identified, sensory time waveform data is validated for quality and recorded to local on-board storage and placed in an out box directory for later transfer onto the network.

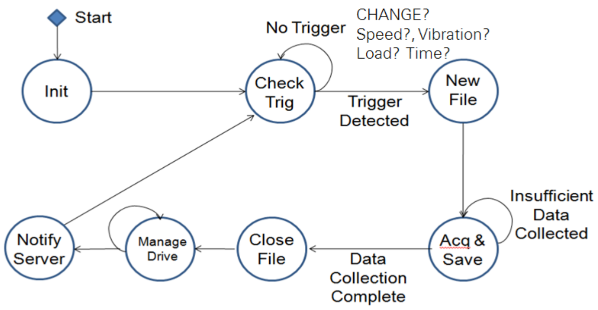

Figure 8. Data acquisition system software diagram

A server class computer, also residing on the business network, is responsible for managing the DAANs and retrieving sensory data recordings from them, Fig. 9. It should be noted that the DAAN, when recording data to its local disk, has provided metadata including equipment hierarchy, sensor calibration information, sensor location, time stamps, and other pertinent information to facilitate data search, off-line analysis, and peer to peer comparisons.

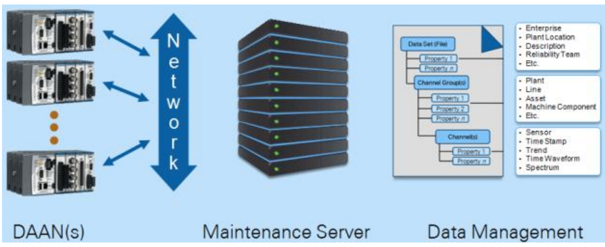

Figure 9. Data acquisition, network, and server

The server has the responsibility of managing all of the DAANs within the network. The server tasks include discovery of monitoring devices, insuring correct configuration of the monitoring devices, managing network and communications security, and monitoring the health of the DAAN as well as the attached sensors. These tasks are performed using both standard and proprietary vendor specific communications protocols to detect, configure, manage, and retrieve data from the DAANs.

The maintenance server has the responsibility of hosting specialist visualization and analysis software. With these tools, vibration analysts in particular can retrieve vibration time waveforms to perform comprehensive visual, graphical, and comparative analytics within a single machine or across machine peers. The maintenance server also has the responsibility of transferring condition indications to the plant historian where DAAN collected condition indicators are later correlated with process and operations data, Fig. 12.

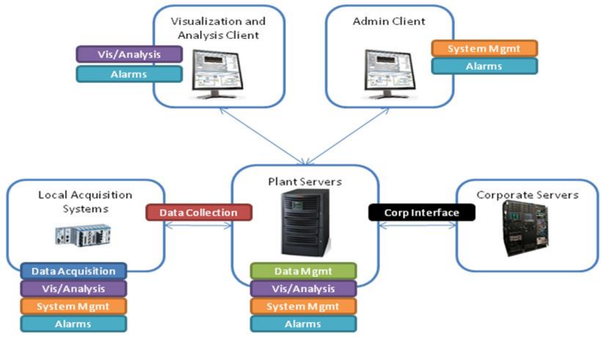

Figure 10. High level architecture of monitoring system

In summary, the networked automatic sensory data collection system performs many tasks. The system resides on a business network, to reduce interference with operations. The DAANs have built in analytics and intelligence to determine when to record sensory data and to determine both sensor and its own operational status and health. The server computer managing the network aggregates sensory data from all DAANs, publishes condition indicators to a plant historian, and provides search, retrieval, and analytics of collected data recordings.

V. Distributed Analytics

A. Overall Analytics Architecture

Analysis of sensory data from the DAANs, and supporting control systems occurs in multiple locations, and ranges from threshold alarms, to advanced signal processing of time waveforms, to automated diagnostics, and health prediction, Fig. 11. To optimize the overall process of tracking equipment health, reliability, and availability; a distributed analytical architecture provides both advanced calculations capabilities and data fusion opportunities.

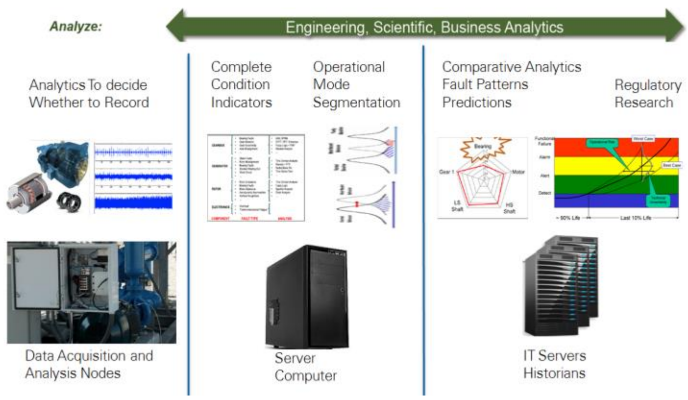

Figure 11. Analytics architecture

The analysis can be broken down into several areas. These include decisions to record and save sensory data recordings, condition indicating calculations, determining the operational state of equipment, peer to peer and fault signature comparisons, prognostics or equipment maintenance projects, and even budget and maintenance schedule optimizations. The location of analytics is often conducted as soon as possible in the sensory information flow, from DAAN to plant historian. If an analysis result can drive a decision to record sensory data, then it should occur in the DAAN. If additional computation power is needed to complete the set of condition indicators for a specific piece of equipment, these calculations can be made on the maintenance server. When comparisons to fault signatures, operational states, and peer equipment are made; these calculations may best be made on either the maintenance server, or after operational data is fused at the plant historian level.

To summarize, analysis of sensory data is made at either the DAAN level, the maintenance server level, or the plant historian and plant wide or corporate level.

B. Calculation of Condition Indicators

To determine when to record data, analysis in the DAAN is conducted in real-time and continuously to determine if a core condition indicator has changed. The analysis in the DAAN includes both vibration analysis and level thresholds. For vibration and similar dynamic sensors, onboard analysis includes true overall, derived overall from a spectrum, crest factor, unbalance harmonics, and mechanical looseness harmonics. Using both dynamic signal analysis and threshold analysis, either dynamic sensory information or static sensory information can trigger a sensory data recording at the DAAN level of the network.

Once the sensory data recording reaches the server, additional condition indicating calculations are performed including more advanced analysis of dynamic sensory time waveforms, Fig 12. These calculations include bearing and gear harmonic analysis, motor current signature analysis, pump vane harmonics, and so on. These calculations can cover a wide range of machinery conditions and indicate a wide range of failure types [7]. The system then supports specific analysis for specific equipment and components, taking advantage of the sensors applied to the specific equipment instance. With the server augmenting the DAAN with additional analysis, a complete set of condition indicators becomes available for each equipment and equipment component.

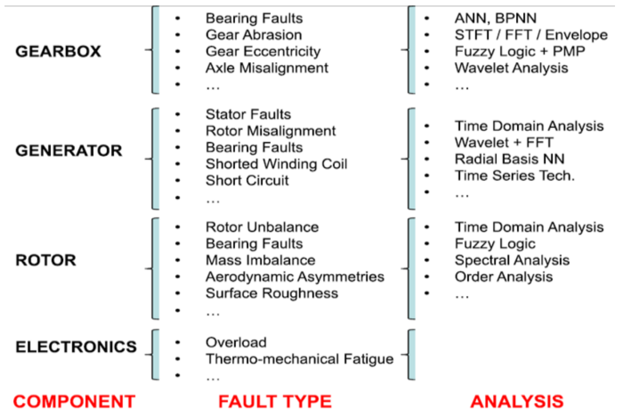

Figure 12. Machinery components, faults, and analysis

C. Finding Patterns Amongst the Condition Indicators

After sorting the condition indicators by equipment type, component type, and operational mode, it is then possible to begin developing patterns from the condition indicators. In many cases, the patterns are first developed for normal or equipment healthy status. Equipment specialists can confirm specific equipment is operating normally with little signs of degradation or reliability. The condition indicators from this normally operating equipment then become an expected pattern of behavior for this equipment under the specific operating conditions.

There are a number of pattern formation tools in the data science and prognostics toolbox, Fig. 12. In practice, the most commonly used technique is the un-supervised tool of anomaly detection. With this tool, a normal set of condition indicators is continuously compared with in-coming sensory data and condition indicators to detect if something unexpected with the equipment is occurring. Anomaly detection can take the form of statistical pattern recognition, quantization errors from expected values, or even logistical regression. The anomaly detection is generally undertaken using condition indicators and process data that have been recorded in the plant historian. If a specific cause is determined, the anomaly then forms a pattern of degradation such as a bearing or gear failure. These patterns are then added to a fault signature database for use in automated diagnostics applications.

D. Automating Diagnostics and Prognostics

With known patterns of specific failure modes, automated diagnostics and predictive maintenance is becoming more possible and probable. Today, there remains a need to validate computer generated recommendations, yet with the advances in data science and predictive analytics, the reliability of automatic diagnostics and prognostics is improving.

For example, given the existence of data driven patterns of bearing, gear, motor, and other rotating component failures; the use of logistic regression (and other techniques) to compare selected condition indicators with fault signature patterns can yield both a specific degradation mode of the equipment, and by trend analysis a likely number of working hours before maintenance is needed.

Visualization tools, including the health radar chart, Fig. 13, provide a visual overview of the current state of health of specific equipment. Sequential comparison of condition indicators for each fault type, or comparison by other correlation techniques, help distinguish between normal patterns of condition indicators and process parameters and those patterns indicating specific failure modes. There are a number of techniques in use today, both in research and in commercial products. Within the power generation industry, anomaly detection is provided by Instep Software's PRiSM™, General Electric's SmartSignal™, General Physics EtaPro™, and other trend analysis products.

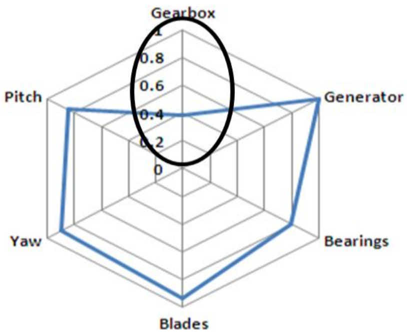

Figure 13. Health radar chart indicating component health

VI. Lessons Learned at Duke Energy

A. Current Implementation Status

Duke Energy has deployed DAANs, condition indicating analytics, as well as anomaly detection and visualization tools within several of their power generation plants in North America, Fig. 14. Each of these plants has deployed 20 or more DAAN nodes per power generation block. Each plant has a server managing the DAANs, calculating condition indicators and reporting these condition indicators to the OSIsoft PI™ Historian. Instep Software's PRiSM™ software is at work building data driven models of normal behavior for anomaly detection.

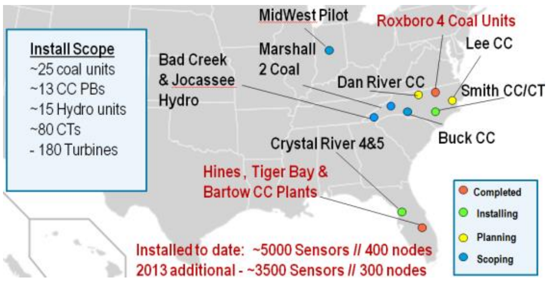

Figure 14. Current fleetwide monitoring at Duke Energy

B. Core Lessons Learned At Duke Energy

Deployment of automated sensory data collection on the fleetwide scale requires significant resources for planning and implementation. Implementation managers are needed at each facility to manage the sequence, personnel resources, and equipment resources that come together to roll out the DAANs, server software, and enterprise connectivity.

Hardware installations can proceed ahead of software installation, especially identification of sensor types and locations and the subsequent installation. Server installations should be timed to coincide with DAAN installation. Once sensors and DAANs are installed, a validation process is needed to validate sensory measurements and calculated condition indicators match traditional manual based activities.

As the anomaly detection occurs on the OSIsoft PI™ Historian, validation on both condition indicators and PI representation of the condition indicators must occur prior to building data driven models. This is similar to any data science or predictive analytics application, data integrity is of high importance.

All sites are excited and bought into the prospect of automated data collection, and assisted and automated diagnostic and predictive techniques. Site persons continue to ask for more automation, more sensory types, and greater equipment coverage. Regular implementation process meetings focused on streamlining the implementation process, and on streamlining feedback are recommended.

The biggest lesson learned is that the system is working as expected. Already visibility of equipment reliability has greatly improved, and plans are now being made to track maintenance savings and availability improvements. With a track record of plant installations, the roadmap for addressing additional plants is established, and can be built upon. Duke Energy is well on its way to complete its fleetwide monitoring and diagnostics center. Duke's efforts promise to result in maintenance savings and availability improvements, while increasing equipment health visibility and optimizing logistics of maintenance.

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