Best Practices Guide: Predictive Maintenance Using Automatic Fault Detection and Diagnostics

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The field of automated building analytics has seen many advancements since it was introduced 20 years ago. Much of the discussion has focused on energy savings, but applications of big data analytics are not limited to this aspect. Lab owners and operators can use analytics not only to improve energy efficiency but also to facilitate predictive maintenance. Predictive maintenance results in increased equipment life, improved reliability, and lower labor cost.

The goal of predictive maintenance is to save money and increase facility reliability. The risk of equipment failure can be reduced by continuous, automated analysis of equipment performance to identify faults before they become critical. Predictive maintenance was once limited to high-value capital assets, but modern automation systems allow for collection and storage of vast amounts of data, and low-cost computing power makes it possible to analyze that data.

A successful predictive maintenance program requires investing in a data-rich building automation system, configuration of that system to perform analytics, development of a process and workflow to manage the automatic fault detection and diagnostics (AFDD) results, and training of facilities personnel on the program. The result is a leaner, more efficient lab facility operation, helping to eliminate energy-wasting faults while freeing up funds and labor for other types of sustainability improvements.

Benefits: A Closer Look

Predictive maintenance programs have many benefits. Improved equipment reliability and decreased risk of product loss and process disruptions are among the most important for mission critical applications such as research, pharmaceutical production, healthcare, and manufacturing. The data captured in the process of predictive maintenance analysis can be used for measurement and verification, as well as providing information for compliance reporting, if applicable.

Predictive maintenance and automatic fault detection increase equipment life and lengthen mean time between failures (MTBF). In addition, labor costs are reduced when equipment is only serviced when necessary. Repair personnel and parts only travel when required, rather than on a preventive schedule, reducing the expense and carbon emissions of unnecessary transportation. Finally, in situations where maintenance functions are outsourced to third parties, predictive maintenance analytics facilitate the verification of repairs using actual operating data, allowing verification of vendor and product performance.

A predictive maintenance program aims to identify faults early enough to give the maintenance team sufficient time to confirm the root cause of the problem, efficiently order any needed parts, and schedule and complete the repair before a failure occurs. Predictive maintenance programs therefore support reliability and sustainability goals and can be used to help ensure energy targets are met and to better predict future energy use.

In summary, predictive maintenance programs:

- Reduce labor costs and building energy consumption.
- Increase reliability.
- Mitigate risks of product loss and process disruptions.
- Increase equipment life.
- Reduce accidents that have a negative impact on the environment.
- Reduce unplanned increases in utility costs.
- Provide oversight of outsourced services, and measurement and verification of work completed.

Preventive Maintenance—The Traditional Standard

Preventive maintenance has been the backbone of mechanical and industrial equipment operation for decades. The goal of preventive maintenance programs is to systematically maintain equipment in optimal operation to prevent or mitigate the consequence of equipment failure. When systems are constructed, the designers take note of component lifetimes, operating hours, wear parts, rated cycles, lubrication, and so on. Historically, elapsed time (run hours) has been used as the key driver for when maintenance activities should be performed.

Some examples of routine scheduled maintenance of equipment are:

- Oil, belt, and filter changes.
- Linkage adjustments.
- Valve seat and steam trap replacement.
- Boiler re-tubing.
- Evaporator bundle cleaning.
- Cooling tower water treatment chemical replenishment.

Although preventive maintenance has some benefits, it also has many shortcomings:

- Higher operational costs
  - The maintenance action is performed whether it is needed or not.
  - Labor is inefficiently deployed.
- Increased risk of failure
  - Identification of deviation from normal operation is often limited to visual inspection.
  - Lack of root cause analysis results in untargeted maintenance and persistent failures.
- Inefficient information management
  - Requires equipment knowledge and manual bookkeeping.
  - No lifetime asset performance information is generated.

Preventive maintenance programs have frequently been automated by traditional computer maintenance management software (CMMS) packages, which require user input of equipment design specifications to create regular schedules for performing maintenance tasks. These are coupled with spare parts inventory information, repair ticket tracking, and enterprise accounting functionality. Most CMMS packages do not provide analytics capability and hence do not automatically ensure optimal control sequences or allow the user to gain institutional knowledge about the performance of assets over time.

Furthermore, today's CMMS packages are unable to measure the effectiveness and reliability of repairs, which are based on the skill level/training of the person performing the corrective action and other outside factors like equipment constraints or resource limitations. In today's world of outsourced operations and repairs, the capability to verify work completed by repair technicians is increasingly necessary for an effective maintenance program.

A strong predictive maintenance program can verify the effectiveness of remediation activities by utilizing measured operational data and models of the machine or system. Measuring the efficacy and persistence of repairs is an important component to iterative management for continuous improvement of processes and assets. Effectively managing and deploying resources, earning utility incentives, and achieving energy targets requires facilities managers, reliability engineers, hired contractors, and so on to have data verification of field work. A predictive maintenance program can be used for the measurement and verification of repairs and provide pre- and post- data for incentives.

Predictive Maintenance (PdM)

Predictive maintenance uses data analytics to detect, and to help correct, equipment faults and operational inefficiencies, with a goal of eliminating the root cause of potential system failures.

Predictive maintenance can include:

- Observation of equipment performance drift.
- Vibration analysis.
- Critical process parameter monitoring.
- Equipment performance during severe weather conditions.

Requirements of an Effective Predictive Maintenance Program

Two elements are needed to deploy an effective, useful, and accurate predictive maintenance program.

- The first requirement is a big data collection and analysis platform that can collect, model, and perform automatic fault detection and diagnostics (AFDD) with root cause analysis. The analytics platform must incorporate domain expertise so that the algorithms have an intended application to the system in question.
- The next critical element is data sufficiency: the availability of data from enough sensors, actuators, and control parameters (for instance, setpoints) so that meaningful analysis can be performed. Equipment design information, such as performance curves, rated cycles, design temperatures, and design flow rates, is essential to understanding how the equipment works.

A system is configured by mapping the sensor data to the AFDD model and by entering constant data or metadata describing the physical characteristics of the system. Sensor data and equipment specifications are needed to build a model, or "digital twin," of the system to be maintained. The figure below shows a visual representation of a digital twin.

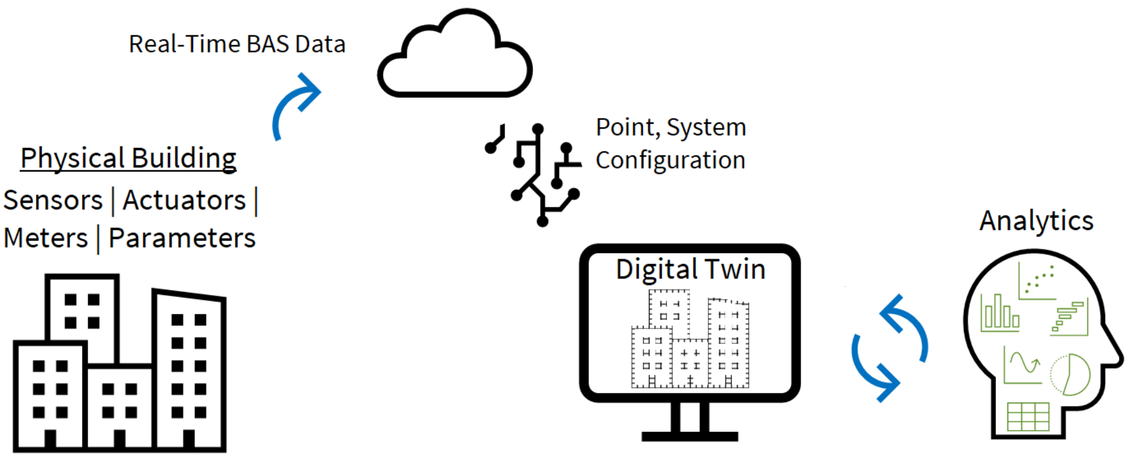

Figure 1: A representation of the Digital Twin model. All images in this guide ©Cimetrics Inc. Analytica 2020

Unlike pure system simulation, this emulation of the process and equipment incorporates the real-world data gathered from the physical sensors and actuators to model actual facility operation. After analyzing the model and real-time data with a series of algorithms, both equipment optimization and predictive maintenance notifications (alerts) can be facilitated.

Figure 2 is an example of the high-level architecture for an automated building analytics solution.

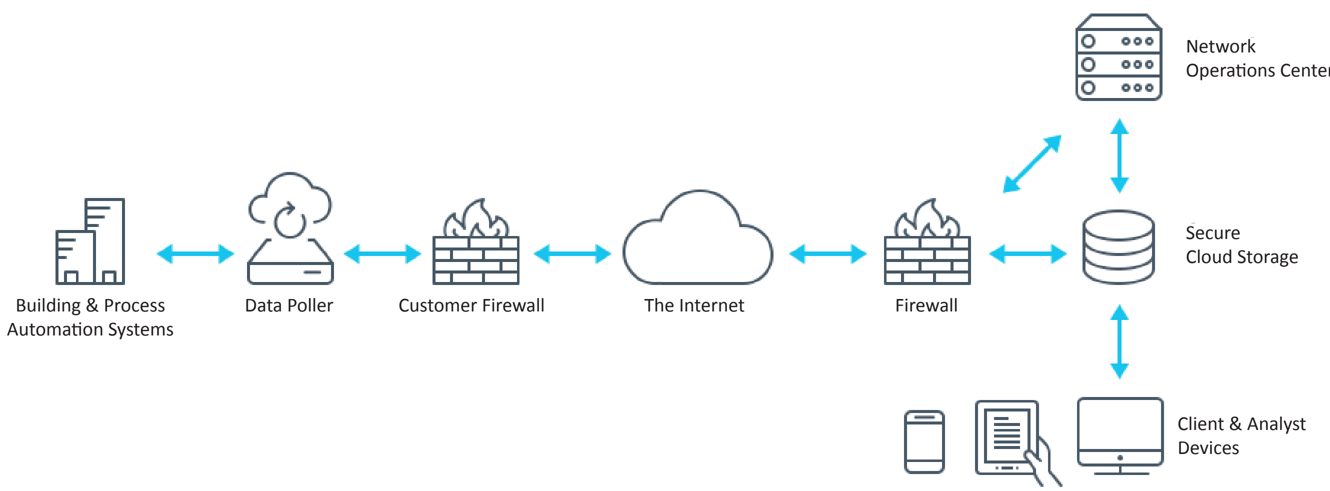

Figure 2: Automated building analytics network architecture

Many original equipment manufacturers (OEMs) have historically kept information about their equipment's design and operating characteristics proprietary. OEMs often do not include sensors on systems because their customers do not perceive the value. Now there is an opportunity for OEMs to differentiate their products by providing a complete operating model as well as sufficient sensors and actuators to provide the data for predictive maintenance analytics. Predictive maintenance can give OEMs greater impetus to provide a new level of data sufficiency.

Predictive maintenance platforms can work in several ways. In their most rudimentary form, these platforms can be used to collect data when the machine or systems are working in steady state (typical operation) to create a baseline. Then statistical comparisons of current operation are compared to the baseline to determine whether equipment performance is drifting. This is useful for detecting system faults, but generally not as good at determining root causes.

With model-based automatic fault detection and diagnostics, the analytics system has a preconceived model of operating characteristics and, using real-time data and sophisticated algorithms, the system can predict where—and sometimes when—those failures might occur.

- Examples of simple statistical process control techniques for predictive maintenance:
- Comparison of operating chiller performance to OEM predictions (design curves).
- Monitoring of machine temperatures, oil viscosity, oil pressure, or water pressure.
- Differential pressure measurements on filters and pumps.
- Pump head pressure measurements.
- Vibration analysis.
- Infrared thermography.

The Keystone of PdM: Automatic Fault Detection and Diagnostics

Whereas preventive maintenance programs rely on design data, run-hours, and CMMS to schedule maintenance before failure, predictive maintenance programs use AFDD to eliminate the root cause before failure. AFDD and predictive analytics can be added to traditional preventative maintenance plans to help prioritize maintenance actions, identify faults that are otherwise undetectable by typical methods, and support facilities maintenance staff when equipment counts and complexity make manual continuous surveillance of equipment impossible.

What Is AFDD?

AFDD uses data analytics to detect and diagnose the root cause of equipment faults, operational inefficiencies, and potential system failures. Large facilities use building automation systems (BAS) to manage heating, ventilation, and air conditioning (HVAC) equipment. A remote continuous building monitoring platform gathers real-time information from thousands of points (sensors, actuators, valves, and software/programs) throughout an HVAC system, as well as potentially thousands more computed and virtual points and static equipment design data. This data is organized into a system-wide digital model of the site that includes information about the interconnectivity of HVAC systems, equipment design specifications, intended sequences of operations, and environmental conditions.

Fault detection and diagnostics algorithms, or rules, are automatically and continuously computed on this system-wide point model, to analyze the data and provide prioritized recommendations for maintenance, reducing energy and ensuring comfort. Faults uncovered through AFDD can include detecting equipment operating outside of intended schedules or sequences of operation, mechanical failures, BAS point configuration or data errors, or suggestions for improved or more efficient control strategies.

Four key components to the AFDD operational technology must be addressed if the resulting software architecture is to be robust, secure, and scalable.

- **Universal connectivity to complex networked systems** found in buildings, including legacy systems, modern building automation data, and meter data from otherwise incompatible and proprietary systems.
- **Automated and continuous fault detection and root cause analysis** with machine learning-based analytics that utilize in-depth domain knowledge of engineered systems and that can be continuously updated and customized for complex real-world equipment and systems.
- **Big data collection and storage**, including data integrity, data conditioning, and data sufficiency, while meeting IT department and security requirements.
- **Topological system modeling** that maps the relationship between terminal, air distribution, central plant(s), and lab equipment, and the spaces and processes they serve. A comprehensive topology promotes accurate fault diagnostics within a piece of equipment and holistic fault detection in whole-building and campus-wide systems.

Big Data for Systems-Level PdM

Although it is significantly more complex than preventive maintenance, predictive maintenance is not a new topic. Historically, thermography and oil analysis have been done, temperature and pressures have been monitored, and, occasionally, vibration analysis has been applied to rotating equipment for the purposes of predicting failure. What is new is the ability to gather and process much more physical data than in the past. By using modern big data approaches, which apply specialized algorithms to system models, the effectiveness of predictive maintenance is greatly increased.

Historically, predictive maintenance has been limited to individual pieces of high-value equipment or “islands of automation,” but now with big data analytics, predictive maintenance is possible at the systems level. By having big data sets from sensors all around the process and equipment, we can build a composite view of systems operation and even correlate maintenance data to the building comfort level or the integrity of lab operations.

Today, we can automatically collect and analyze enough data so that predictive maintenance can be scaled down to the low-cost ubiquitous devices and sensors in a system and be applied to small end- point devices, such as variable air volume boxes, and process utility connection points, such as water for injection and compressed air connection points.

Driven by automatic fault detection and diagnostics, predictive maintenance can detect even minor anomalies and failure patterns to determine the assets and operational processes that are at the greatest risk of failure. This early identification of issues helps facility managers deploy limited maintenance resources more cost-effectively and maximize equipment uptime.

Examples of Predictive Maintenance Findings

Example 1: Air Filter Replacement

A straightforward example for comparing preventive vs. predictive maintenance is air filter replacement. Preventive maintenance attempts to estimate an average life of a filter and, perhaps enabled by a CMMS, deploys maintenance staff to replace the filter at intervals that are shorter than this average life. This implies that some filters will be replaced prematurely, and some will be replaced too late.

With predictive maintenance, measured differential pressure across a filter can be used to calculate the optimal time to replace the filter. The predictive maintenance system automatically monitors the filter as it loads up with dirt over time (differential pressure increasing) and triggers a maintenance action at the right time. When the filter is replaced, the differential pressure drops, thereby verifying that the replacement was done correctly. By analyzing the pressure drop across the filters over time, an optimal filter replacement process can be established. Further, information can be gleaned regarding which filter manufacturers' products perform best in each condition. Consider the benefits of this predictive approach when the air filter in question is serving a cleanroom, where mistakes can translate to particulate contamination, operational disruptions, and potential product and/or research loss.

Figure 3 shows an example of the differential pressure increasing across an air filter. The differential pressure alarm in the BAS begins to flag immediately after the differential pressure increases above setpoint (a value of 1 indicates the point is in alarm). Sensitivities in the BAS cause the alarm to oscillate between ON and OFF for weeks before the alarm remains ON. Persistent alarms are then often untrusted and ignored. Traditional corrective maintenance would potentially result in fan filter replacement immediately after the initial transient alarm.

The plot in Figure 3 shows the differential pressure slowly building up over the course of several months after the initial alarm, while remaining within the manufacturer's specification. In this example, optimizing the interval between air filter replacements would result in $900/year of energy and material savings. Typical payback periods of issues identified through AFDD are less than 1 year, and many faults identified are associated with low-cost changes. Modeling the system using data analytics predicts fan filter replacement periods that minimize total accumulated cost of the dirty air filter, resulting in improved resource management.

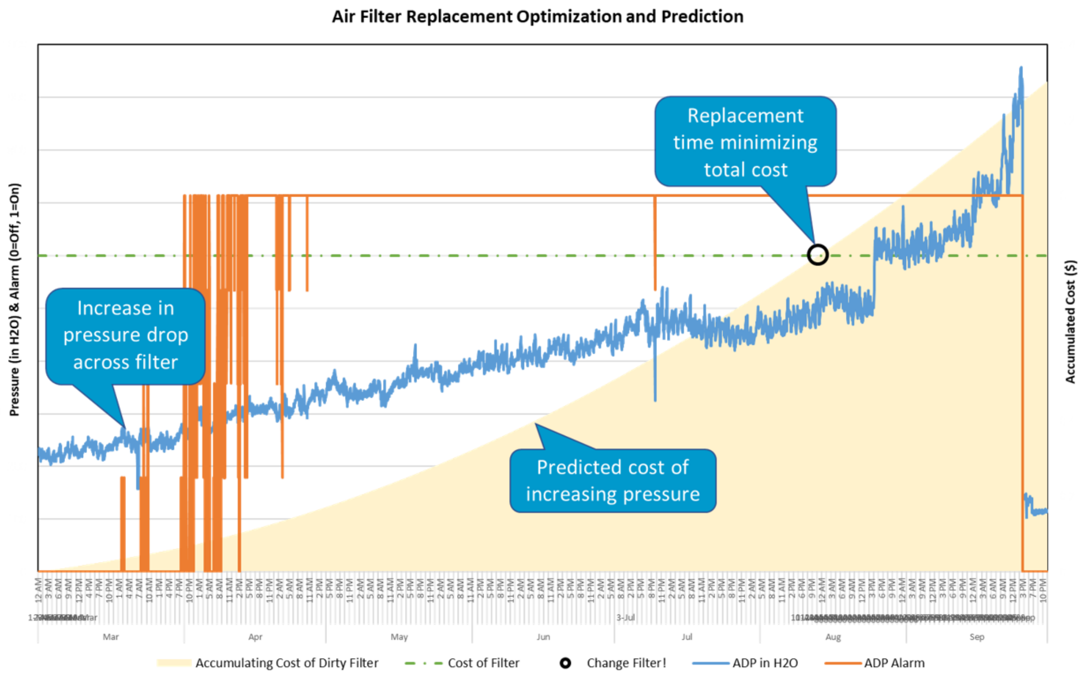

Figure 3: Air filter replacement optimization

This example highlights the importance of the AFDD platform to perform data conditioning, which includes recognizing and excluding anomalous data (for example spikes), interpolating gaps in data to model continuous trends, and differentiating between transient and persistent faults. In addition, the AFDD platform should ensure data integrity, or accuracy. Faulty sensor data can override intended control strategies and result in false flags or missed opportunities.

For example, a faulty differential pressure alarm that does not accurately flag dirty filters can have safety implications, or a poorly located occupancy sensor can repeatedly trip and cause zone equipment such as fume hoods to run unnecessarily. The AFDD system needs to be able to recognize sensor errors, calibration issues, poor sensor location, and BAS point configuration errors. Ongoing sensor maintenance is required for accurate readings, and points are frequently mapped and remapped.

Example 2: Actuator Oscillation

Figure 4 shows an example from a 250,000-square-foot research laboratory in New England. This example demonstrates the significance of identifying rapid oscillation for equipment life as well as the importance of communication and coordination in issue resolution. The predictive maintenance program model, driven by AFDD software, identified an oscillating preheat valve actuator on an air-handling unit by analyzing the frequency and range of oscillation and how long the fault was occurring.

The building automation system service technician inspected the unit and found the valve leaking at the stem. An accurate AFDD platform and ongoing communication throughout the chain of command paired with site verification builds trust in the predictive maintenance program. The valve completely failed after the oscillation was originally detected; the normally opened preheat valve failed open, adding more than 30°F of excess heat to the supply air.

Valve actuator oscillation and the resulting valve failure are particularly insidious because the discharge temperature setpoint is maintained, making this issue difficult to detect without analytics. Repair of the leaking valve resulted in approximately $170,000 in annual cost savings from avoided cooling and heating energy.

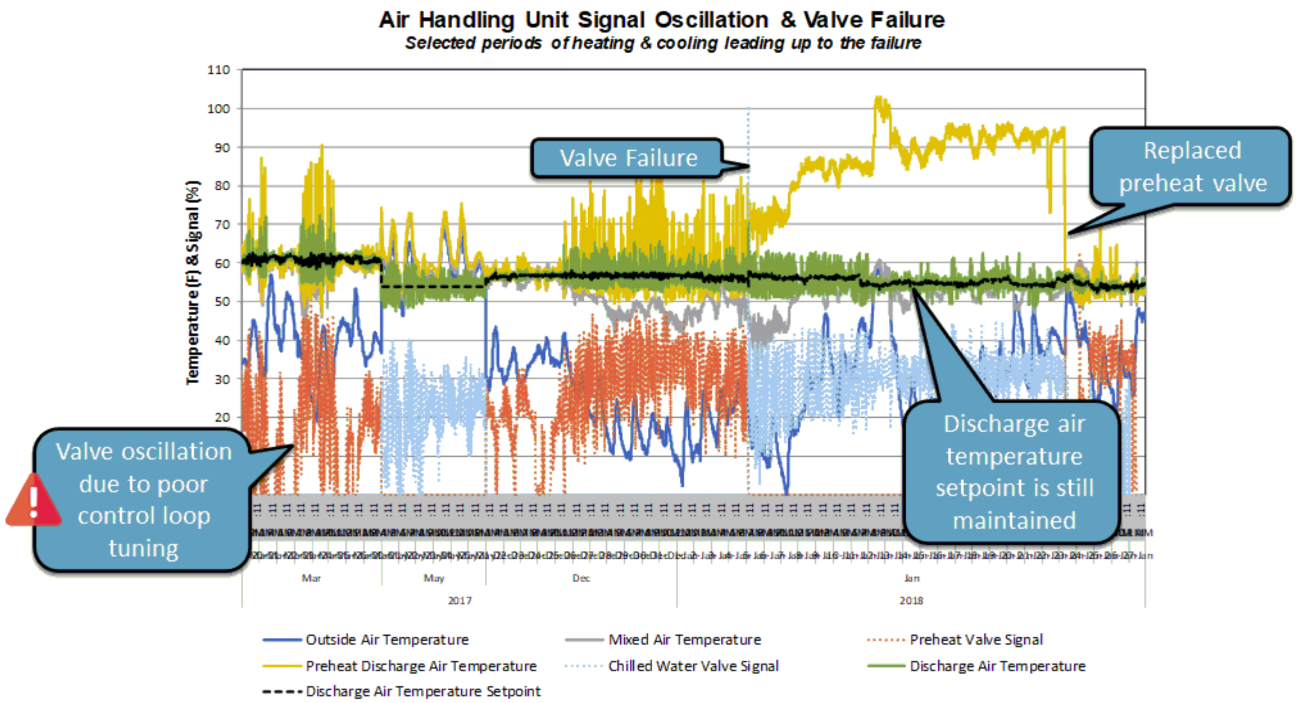

Figure 4: Equipment oscillation and failure

System cycling can have several potential root causes. Valve hunting is often a result of poor temperature control loop tuning or improper use of autotuning functions. Loop tuning may have been performed incorrectly, especially if challenges exist that require advanced tuning methods.

Valve oscillation and simultaneous heating and cooling can also be caused by conflicting setpoints. For example, energy is introduced to the airstream by equipment such as supply fans and increases the temperature of the supply airstream; therefore, the mixed air temperature setpoint and all coil discharge air temperature setpoints must agree and take this additional heat into account. A dead-band, or range between each setpoint, would ensure that valves do not “hunt” and oscillate trying to maintain setpoints too close in value. The AFDD algorithms should factor in calibration errors and thresholds, for example to account for the temperature rise through ductwork, and to ensure data integrity.

Fault detection and root cause analysis are dependent on data sufficiency. Remediation is streamlined through targeted root cause analysis. In the absence of robust data, sophisticated artificial intelligence can classify multiple symptoms into a decision tree and prioritize possible root causes. A good example of data insufficiency is in a unit that is simultaneously heating and cooling. Without a mixed air, preheat discharge air, or cooling discharge air temperature sensor, the root cause and the degree of excess heating and cooling cannot be determined. Data insufficiency makes root cause analysis difficult, and, therefore, remediation is more involved. It is more costly to have facilities personnel go inspect the unit and do a detailed deep dive into the root cause.

ASHRAE has codified the importance of data sufficiency in Guideline 36; the purpose of this guideline is to provide uniform sequences of operation for HVAC systems to maximize energy efficiency and performance, provide control stability, and allow for real-time AFDD.

Conclusion

The big data analytics revolution has enabled true predictive maintenance on a large scale. Users of predictive maintenance analytics can now reap the benefits of cost savings and reduction in greenhouse gas emissions, increased reliability, prolonged equipment life, and reduced risk of process disruptions. A future opportunity to further increase the effectiveness of predictive maintenance systems is integration with enterprise asset management systems. Although this may seem simple at first, there is currently a need for a human decision maker to add business insight as to what maintenance investments should be made.

In addition, multiple projects are underway in the industry to standardize building automation system point naming and metadata structuring and topology. Many exciting opportunities lie ahead, and we are just scratching the surface of what is possible with physical world data analytics.

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