Wind Farms Operational Intelligence

Data-Driven Approaches to Enabling Operational Intelligence for Wind Farms.

Emerson's Data Management practice implementations allow clients to make educated, site specific production and operational decisions based on the analysis of real time data from integrated field and plant systems.

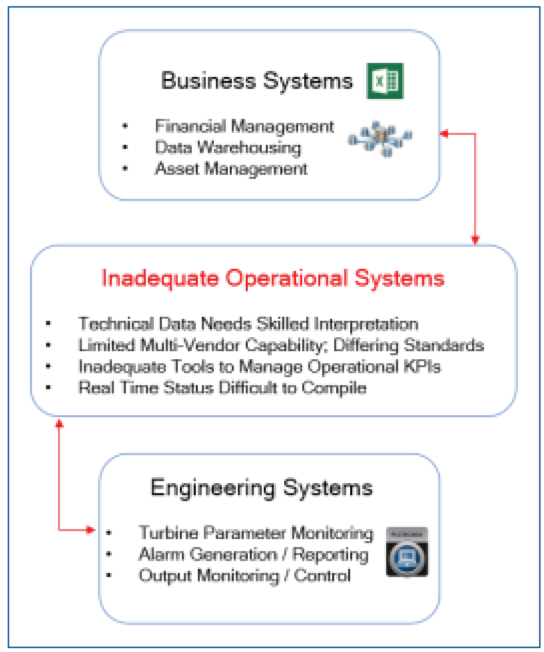
Table of Contents

How Can Emerson Help Production Data Management?

It has been estimated that $US 8 trillion of investment will flow into the wind energy sector globally over the next 25 years (Wind Energy in Alberta, 2015). The global demand for wind energy will rise as the world tries to move towards renewable energy sources. Wind energy producers have historically faced several challenges in gathering operational insight in order to optimize operations. Poor multi-vendor data capability, manual and error-prone analysis and reporting, cumbersome access to SCADA data, and inconsistent and labour intensive wind farm event monitoring are some of the challenges that operators have faced historically (Operational Intelligence for Renewable Energy, 2010). Modern technology presents significant opportunities for wind energy operators which will alleviate many issues and enable a proactive, data driven operating platform through data analysis and real-time reporting. The Data Management practice for Operational Certainty Consulting specializes in designing, implementing and supporting real-time, historian based, reporting and integration solutions for Oil/Gas and Utility companies.

Challenges and Opportunities

Historically, wind energy operators have faced limitations in an evolving organizational landscape where business systems have been unable to make sense of data provided by engineering systems in an operational support systems layer to be able to gain a significant competitive advantage. Below are common challenges that operators often face (Operational Intelligence for Renewable Energy, 2010):



- Turbines from different vendors have different standards, instrumentation naming and consolidating the data in a consistent and comparable format has been challenging
- Data analysis and interpretation has been more of a manual and error-prone task that falls in the hands of technical resources
- PIs and benchmarks are not centralized for access and achieving real-time insight is difficult since most of the analysis is manual and there are large volumes of data to sift through
- Access to SCADA data is cumbersome and inconsistent
- Event monitoring and logging is a manual and error-prone process

Opportunities

A more robust operational systems support layer would allow for several possibilities. For instance, organizations could:

- Graphically represent wind farm operations
- Identify changes in power performance and perform forensic analysis to determine cause of issues
- Assess power availability
- Quantify energy gains and losses
- Estimate long-term energy

Over time, these capabilities would translate into significant cost reductions by optimizing turbine performance, minimizing disruptions and downtime, and adopting an overall proactive operational foundation (Graves & Harman, 2007).

Big Data and Iot

With improving system communications and data handling capabilities, wind energy producers have significantly more granular and frequent data to contend with. This presents an added opportunity as it opens the doors for more detailed thorough analysis (Hummel, 2015). The Internet of Things is emerging as the next major technological trend. By connecting to the Internet billions of everyday devices – ranging from fitness bracelets to industrial equipment – the IoT merges the physical and online worlds, opening a host of new opportunities. In the industrial world, IoT is not considered a groundbreaking trend as SCADA systems have permitted connectivity from remote devices (Dingman, 2015), but the industry has seen improved quality and reliability of network infrastructure that allows for advanced management at wind sites. Modern industrial grade networking equipment provides a high degree of reliability and control pertinent to smart energy management systems and offers innovative software management features that enable a diverse network of connected devices (Froese, 2016). Fundamentally, however, a foundational operational system support layer based on the principles of data analysis must be instated first to allow organizations to position themselves to further benefit from the trends.

Data Analysis Procedures

The following section discusses some analytical procedures which can be applied in order to resolve problems and target the opportunities mentioned in the previous sections.

Downtime Analysis and Reporting

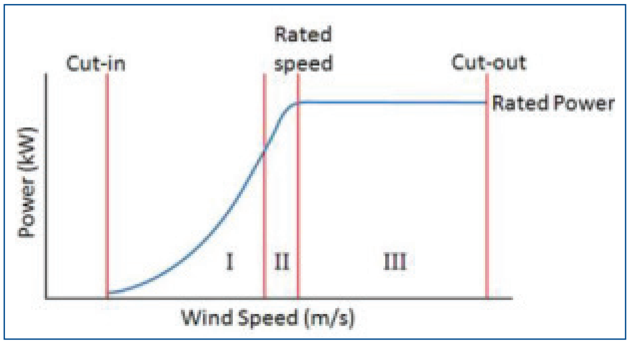
Downtime logs are typically recorded manually however the logs do not always cover 100% of events as there are unplanned outages that can be missed (Singh, 2013). A robust downtime event recording system is beneficial as it provides a journal to cross check manual entries. Furthermore, downtime reporting can give insight into the breadth and impact of various events and view the data from different perspectives (e.g. geographical, or by turbine manufacturer, or by fault code). An automated downtime event reporting system can help monitor and capture the following parameters:

- Total duration of downtime events
- Total quantity of downtime events
- Fault reason code
- Human comments
- Geographical information

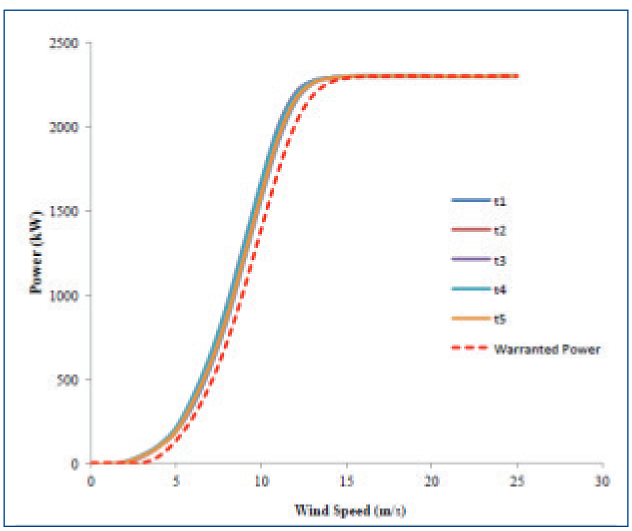
Accurate downtime reporting can back up manual logbook data and provide a tool for root cause analysis when analyzing changes or deviations in turbine performance.

Power Curve Analysis

Background Power curve analysis is one of the fundamental data analysis practices for wind farm operators. Active power production depends on wind speed and rated turbine efficiency. The power available is a function of the wind frequency distribution in an area (the number of hours that the wind blows at a particular speed in a certain area) and the total available power in the wind (a function of the air density, area that the wind passes through, and wind velocity) (Singh, 2013).



As a reference, wind turbine manufacturers also typically provide a rated power curve which can be used to compare active power outputs. A typical power curve is shown to the right. At wind speeds in region I, the turbine is run at maximum efficiency to extract as much energy as possible. In region II, the wind speeds are such that the turbine is able to reach its rated power. In region III, the turbine is controlled such that the energy extracted remains at the rated power. After the cut-out speed, the turbine will shut down as high wind speeds could damage the turbine (Singh, 2013). Actionable Insights Turbines measure power output and wind speed, and this data is typically fed to the SCADA system. Thus, is it possible to produce a power curve XY plot depicting the actual turbine performance. The manufacturer's power curve can then be compared with this curve to identify turbine performance issues. For instance, the manufacturer's power curve can be plotted against actual power curves for all turbines in a wind farm

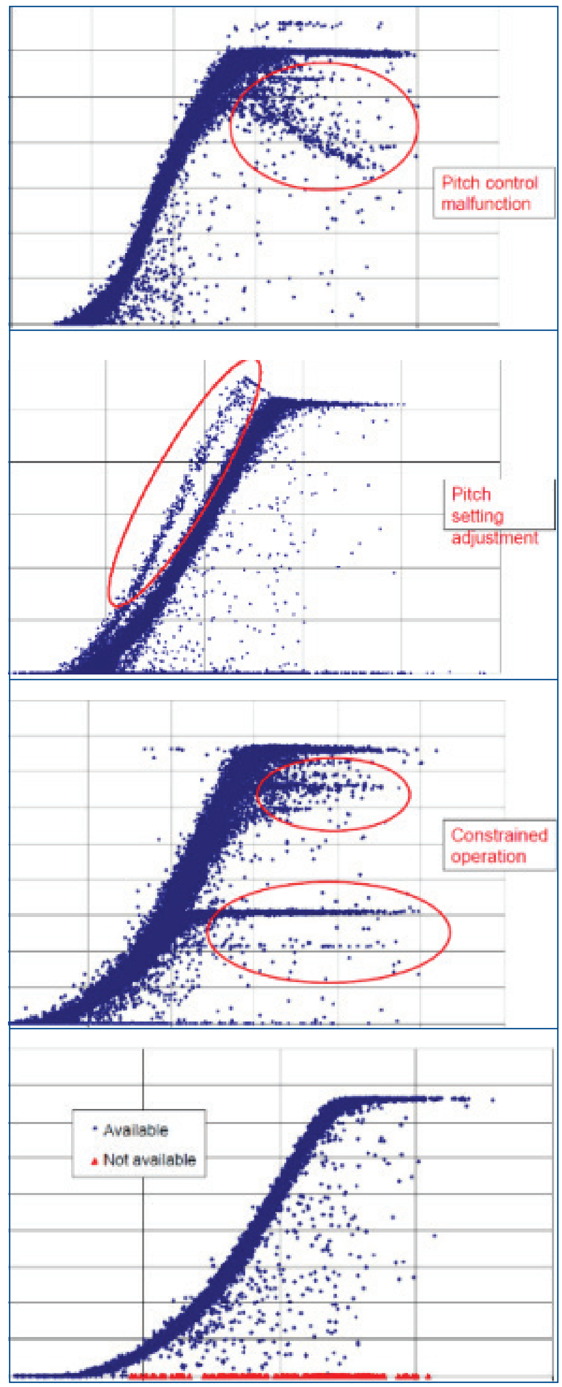


- Any turbines whose power curves appear significantly to the left of the manufacturer's curve can be flagged down for further investigation as these turbines are underperforming. Other KPIs and analyses listed in this article may be performed to further gain an understanding of what is causing the dip in performance.
- Total delta between the warranted power curve and actual power curves can be quantified using statistical methods

including Kurtosis, Skewness, and Squared Errors (Kusiak & Verma, 2013).

- With additional data available, such as wind direction, multi-dimensional analysis is possible by plotting additional dimensions on the chart. This will help identify whether problems are localized to a specific wind direction, hinting at root causes such as wind vane misalignment (Singh, 2013).
- Total delta for each turbine can be tracked over time and deterioration rates may be studied in a predictive manner to encourage preventative maintenance.

Typical Problems Uncovered At a glance, different power curve shapes may hint at different problems but in some cases, data must further be analyzed to determine true root cause. For instance, data may need to be viewed against time to determine if the change in performance profile of a turbine changed after a specific time. The following are typical problems that are uncovered by viewing power curves: Pitch Control Malfunction: Variable speed turbines employ a technique known as active pitch control, where the blade pitch angle is adjusted to increase capture of power given wind speed (Melicio, Mendes, & Catalao, 2009). In the case of malfunction, power production is suboptimal as wind increases due to a failure in the adjustment system. Pitch Setting Adjustment: A related problem to pitch control malfunction is having an incorrect setting applied for pitch configuration. Essentially, the adjustment system is configured for a suboptimal angle, which essentially reduces the power produced in comparison to the true potential of the turbine. Constrained Operation: There are several reasons that wind turbine performance may be actively curtailed. Turbines should not produce more than the rated power as there is potential for damage (Wind turbine power output variation with steady wind speed, 2016). There may also be a requirement to curtail power due to grid supply limits (Singh, 2013). Differentiating constrained operation, and understanding lost potential is an important aspect to long term operational intelligence. System Downtime: Downtime can be tracked from the power curves where wind speed is greater than the cut in speed, but the power output is nil. The output of the downtime list can then be compared against operator logs to understand if there was any unplanned downtime. Overall, a calculation can be developed to determine the lost power by determining the difference in values on the Y axis between the actual production and rated production, with respect to the wind speed. By further incorporating energy prices, this will yield an estimate of the lost production revenue caused by downtime (or other issues).



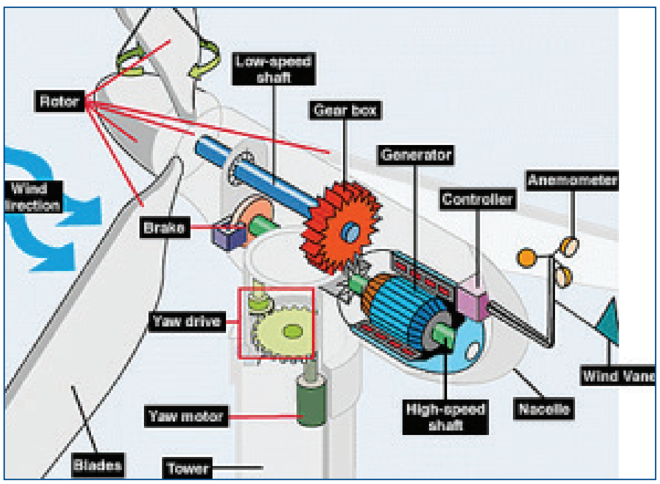
Filtering out Bad Data Oftentimes in the datasets used for charting, bad data is observed. The bad data can be caused by faulty measurement devices and should be filtered out from the analysis to avoid any false results. There are several techniques listed in the literature on filtering out bad data, including heuristics, filtering by standard deviation (Singh, 2013), and using Mahalanobis distances in concert with k-means clustering (Verma & Yang, 2014).

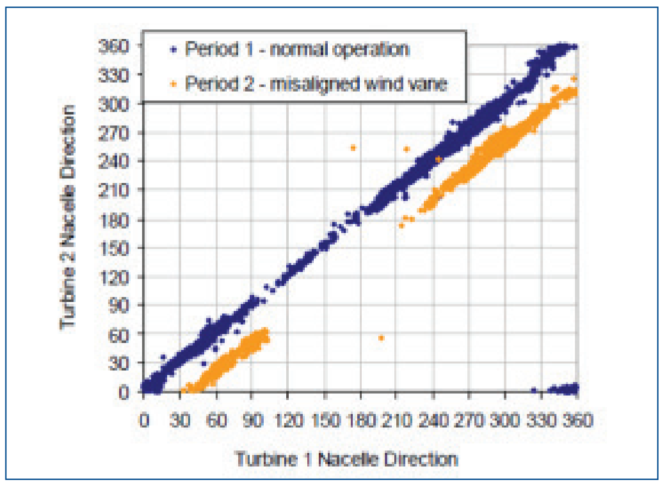
Energy Ratio Analysis

Energy ratio is another way to review the performance of turbines. It is calculated by dividing the active power produced by the theoretical power available (either through derivation via the wind frequency distribution or comparing against the manufacturer's rated power curve). This ratio can be compared between turbines in a wind farm and against other measured operational characteristics such as wind direction, rotor speed, torque, etc. to gain an understanding of whether any particular factor is significant. Over time, thresholds and expected ratios can be determined for each turbine and operational alerts can be triggered if the ratios fall under the expected values (Singh, 2013).

Yaw Alignment Analysis

The Yaw system in a wind turbine is the component that is responsible for the orientation of the wind turbine rotor towards the wind (Yaw system, 2016). The Yaw system closely interacts with the wind vane to determine positioning requirements for optimizing power production. It is very easy for service technicians and turbine installation staff to accidentally induce a yaw misalignment when exchanging or installing a wind direction sensor (wind vane). The vane only has to be misplaced by 5-6mm to cause a 15-degree yaw misalignment, which results in a 5-6% annual energy loss (Optimising annual energy production with apt handling of yaw misalignment, 2013). Wind vane misalignment can be detected by plotting the wind direction measurements of two turbines against each other. In the example curve to the right below we can see that between the 90 to 240-degree range, turbine 1 and 2 do not align on their wind direction measurements, implying a wind vane misalignment between the two. (Singh, 2013). Analyzing these data can be automated and should be performed periodically and ad hoc at any time when there is maintenance completed on the turbine.



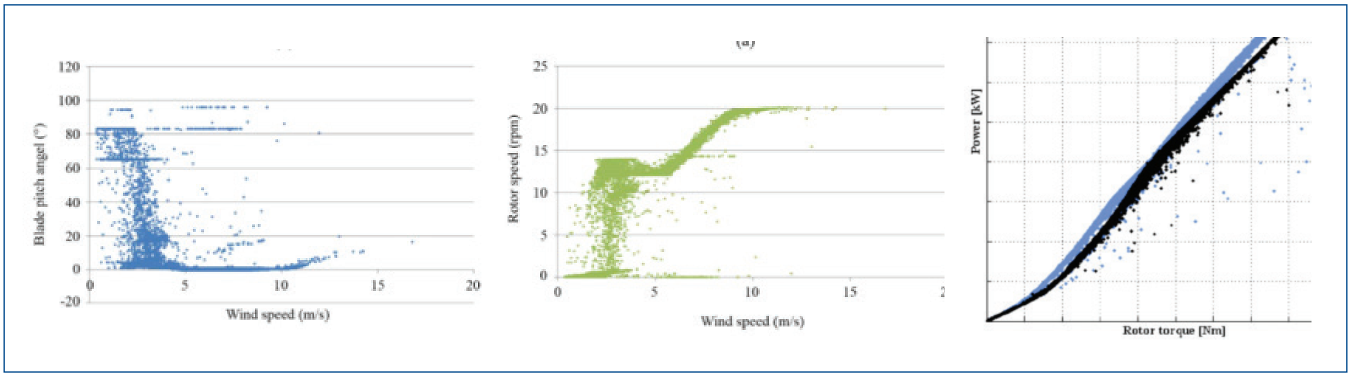


Pitch Curve Analysis

A blade pitch curve shows the relationship between the turbine pitch angle and wind speed. The pitch angle is calculated by averaging angles of three blades. The turbine's control system adjusts the blade angle for maximum power capture. A malfunction of the control system and high wind speed causes a turbine to stall (pitch angle becomes 90). A negative value of the pitch angle reflects the presence of a strong wind. Under normal operation, the blade pitch settings are continuously adjusted by the control system for the maximum power output. The result of a malfunction is suboptimal power production (Kusiak & Verma, 2013). A typical pitch curve is shown to the right. Wind speed can be plotted against blade pitch angle to determine where a malfunction may have occurred. Data query tools may also be employed to determine when the blade pitch angle becomes 90 while the turbine is still operational, or when the pitch angle becomes a negative number.

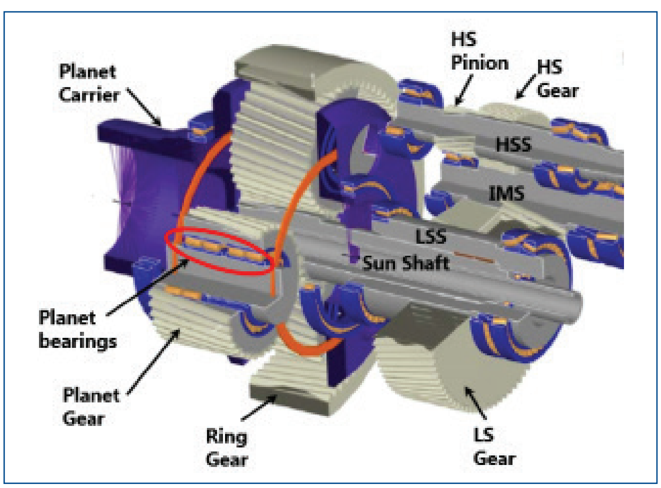
Rotor Curve Analysis

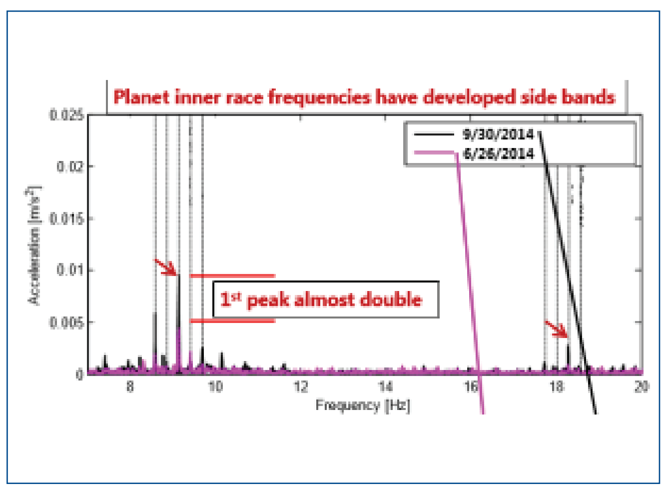
Rotor curve analysis involves plotting rotor speed against wind speed. In general, rotor speed should increase with increases in wind speed after the cut-in wind speed is achieved (Singh, 2013). A typical rotor curve is depicted below. If any differences from a typical rotor curve are observed, subsequent analysis can be performed. This analysis may involve comparing torque used for the rotor in comparison to produced power. Ultimately, the torque utilized to achieve the same power output should be consistent and any change impacting this ratio over time should be investigated. Below to the right is a graphical example of a deterioration in rotor performance tied to an operational event (Singh, 2013). In this case, an unsuspected operational event degraded the rotor system such that more torque was required to achieve the same amount of power production.



Gearbox Performance Analysis

Gearbox failures are one of the most expensive repairs on turbines, costing upwards of $350K per failure (McNichols, 2014). Planet bearings are the component of the gearbox which has the most significance on gearbox life. Premature planet bearing failure is typically caused by debris, assembly errors, load sharing, or material defects. Data analysis of planet bearing components can provide indicators which can help detect or even predict failures in planet bearings. Planet bearing acceleration can be plotted against frequency over time as a categorical dimension to determine if there is any upward trend in the acceleration at the same frequency (Ganeriwala, 2010). If there is, this is an early warning sign that damage inspection and preventative maintenance should occur (McNichols, 2014).





Predictive Analysis

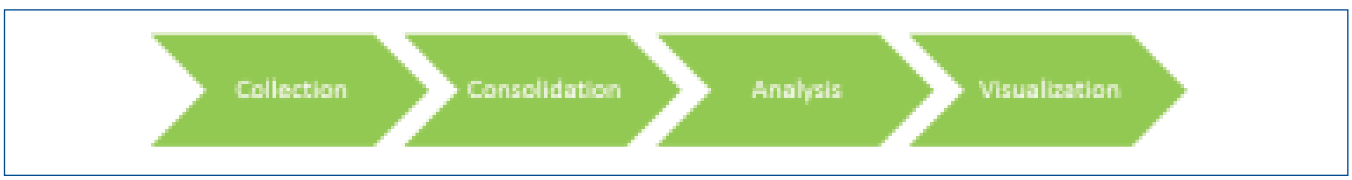
Predictive analytics can be applied to the analysis techniques. By using statistical techniques to extrapolate the listed measures and compare predicted values versus actual values. Once a model has been defined and trained, it can be used to accurately predict results based on current operating conditions and historical performance (Harte, 2014). There are a variety of software tools and languages to aid in this. Naturally, organizations must understand and master available data analysis methods prior to navigating predictive analytics.

Summary

The previous sections identified several data analysis methods possible with the availability of operational data. A holistic operational analysis and monitoring approach should be put together where a combination of automated information and exception reporting and sufficient manual data analysis should be completed in order to improve and optimize turbine performance. While some data analysis exercises may be executed every day, other data analysis tasks should be performed at a lesser frequency. Overall, the portfolio of analytical tools will be driven based on organizational requirements but consolidating the data into a unified and consistent view and automating the analysis will provide a strong foundation for an agile organization.

The Emerson Advantage

We are a technology agnostic organization and help our clients achieve high performance by tailoring the solution to their needs. We have a flexible methodology and assist our clients in implementing a range of solutions ranging from completely packaged to completely custom. Enabling operational intelligence is a multi-step process and we have the experience and technical know-how to help with each step.



Collection We can help you get operational data from an array of diverse data sources through several different industrial protocols, such as OPC or Modbus. Having worked with several diverse SCADA systems we can help bring the data into historian systems such as OSIsoft PI or Capstone DataParc or corporate data warehousing systems such as Oracle, SQL Server or SAP. We can help set up collection methods that are resilient to network issues, and data collection can be compressed to save network bandwidth. Consolidation Typically, plant or PLC based instrumentation is tag based. We can help your organization achieve a unified view of the data by employing a meta-data abstraction layer so that you can talk “apples to apples” regardless of turbine vendor and instrumentation differences. With software such as PI Asset Framework, tag/instrument-based data can be viewed as an asset-centric model. This metadata model provides a foundation for data analysis and analytical reporting. Our solutions allow end to end technological integration such that all areas of the company can consume the archived data, regardless of the protocol used and supporting backend technology. This enables different departments to have a consistent, “single source of truth” view of the data coming out from all wind turbines across all wind farms. Analysis We are well versed in various analytical software tools which help study the data and determine key performance indicators. Out of the box tools such as OSIsoft’ s PI Analysis Service, Capstone ParcView, or Microsoft Analysis Services can help understand and dissect the data from different perspectives. Traditional desktop analytical tools such as Microsoft Excel can also be turbo-charged to perform complex analytical tasks using PowerPivot or Visual Basic. If an off-market analysis framework does not fit your needs, we provide custom software development services as well. As an extension of the analytical capabilities we can also set up real-time exception reporting to alert you when excursions occur. Out-of-the-box tools like PI Event Frames can be used to automatically capture events based on pre-defined triggering rules.

Visualization we can help you implement leading edge visualization tools to help distribute your data. We can help with a broad range of visualization tools including business intelligence tools such as Tibco Spotfire or Tableau, traditional reporting tools such as Crystal or Microsoft SSRS, or time-series visualization tools such as PI Coresight, ProcessBook, ParcView. Many of these tools contain built-in statistical analysis capabilities to complement the analytical tools mentioned above. As always, if there is nothing that fits your requirements, we can provide custom software as well.

Want to Learn More?

Bhattacharya, P. (2010, June 1). A Study on Weibull Distribution for Estimating. Journal of Applied Quantitative Methods, 5(2), 234-241. Retrieved from http://jaqm.ro/issues/volume-5,issue-2/pdfs/bhattacharya.pdf Dingman, S. (2015, May 29). Beyond the smartwatch: Canada finds its place in the Internet of Things. Retrieved from The Globe and Mail: http://www.theglobeandmail.com/technology/internet-of-things/article24668935/ Dudgeon, G. (2013, March 1). Big Data Means Big Insight for Wind Farm Operations. North American Wind Power. Retrieved from http://nawindpower.com/online/issues/NAW1303/FEAT_04_Big_Data.html Energy Production Estimating. (2014, October 1). Retrieved from Northern Power: http://www.northernpower.com/wp-content/uploads/2014/10/NPS-White-Paper-Energy-Production-Estimating.pdf Froese, M. (2016, April 19). Talking with turbines through the Internet of Things. Retrieved from Wind Power Engineering: http://www.windpowerengineering.com/design/electrical/controls/wind-farm-networks/talking-turbines-internet-things/ Ganeriwala, S. (2010). Review of Techniques for Bearings & Gearbox Diagnostics. IMAC Conference. Jacksonville: SpectraQuest Inc. Graves, A., & Harman, K. (2007). Operating Wind Farm Monitoring and Performance Optimization. Wind Turbine Reliability Conference (p. 9). Garrad Hassan. Gray, C. (2012, November 1). Efficient Wind Farm Performance Analysis & Optimisation. Retrieved from Uptime Engineering: http://www.uptime-engineering.com/downloads/EcoPower_Academy_Copenhagen_GRAY_Nov2012.pdf Harte, M.-J. (2014, March 5). How predictive analytics improves wind turbine maintenance. Retrieved from Algorithmic: http://algoritmica.nl/how-predictive-analytics-improves-wind-turbine-maintenance/ Hummel, M. (2015, September 10). The Future of the Internet of Things in Renewable Energy. Retrieved from Renewable Energy World: http://www.renewableenergyworld.com/articles/2015/09/the-future-of-the-internet-of-things-in-renewable-energy0.html Kalmikov, A., & Dykes, K. (2010, January 1). Wind Power Fundamentals. Retrieved from MIT: http://web.mit.edu/windenergy/windweek/Presentations/Wind%20Energy%20101.pdf Kellner, T. (2015, September 27). Wind in the Cloud? How the Digital Farm Will Make Wind Power 20 Percent More Efficient. Retrieved from GE Reports: http://www.gereports.com/post/119300678660/wind-in-the-cloud-how-the-digital-wind-farm-will/ Kusiak, A., & Verma, A. (2013). Monitoring Wind Farms with Performance Curves. IEEE Transactions on Sustainable Energy (Volume 4, Number 1), 192-199. Retrieved from http://user.engineering.uiowa.edu/~ankusiak/journal-papers/wind_ieee_2013.pdf Mahalanobis Distance. (2016, March 4). Retrieved from Wikipedia: https://en.wikipedia.org/wiki/Mahalanobis_distance McNichols, C. (2014, February 27). Wind turbine Gearbox Condition Based Maintenance Equipment and Challenges. Retrieved from Romax Technology: http://canwea.ca/wp-content/uploads/2015/03/Session-8-Colin-McNichol.pdf Melicio, R., Mendes, V., & Catalao, J. (2009). A Pitch Control Malfunction Analysis for Wind Turbines with PMSG and Full-Power Converters: Proportional Integral versus Fractional-Order Controllers. Covilla: University of Beira Interior. Retrieved from http://webx.ubi.pt/~catalao/EPCS_Melicio_revised.pdf Operational Intelligence for Renewable Energy. (2010). Retrieved from ServusNet Informatics: http://www.ucd.ie/t4cms/ti12_d.farren_servusnet_11jun10.pdf Optimising annual energy production with apt handling of yaw misalignment. (2013, November 4). Retrieved from Wind Energy Update: http://analysis.windenergyupdate.com/operations-maintenance/optimising-annual-energy-production-apt-handling-yaw-misalignment Singh, P. (2013). Analytical Techniques of SCADA Data to Assess Operational Wind Turbine Performance. Glasgow: University of Strathclyde. Vasudevan, V. (2015, January 20). Wind Energy Equipment Manufacturer's Guide to IoT Service Excellence. Retrieved from GlassBeam: http://www.glassbeam.com/wind-energy-equipment-manufacturers-guide-iot-service-excellence/ Verma, A., & Yang, K. (2014). A Data-driven Approach for Wind Turbine Performance Benchmarking. Industrial and Systems Engineering Research Conference. Montreal: Department of Industrial and Systems Engineering, Wayne State University, Detroit, MI. Wind Energy in Alberta. (2015, December 1). Retrieved from Canadian Wind Energy Association: http://canwea.ca/wind-energy/alberta/ Wind Power. (2016). Retrieved from Engineering Toolbox: http://www.engineeringtoolbox.com/wind-power-d_1214.html Wind Statistics and the Weibull Distribution. (n.d.). Retrieved from Wind Power Program: http://www.wind-power-program.com/wind_statistics.htm Wind Turbine Power Calculations. (2016). Retrieved from Royal Academy of Engineering: http://www.raeng.org.uk/publications/other/23-wind-turbine Wind turbine power output variation with steady wind speed. (2016, May 01). Retrieved from Wind Power Program: http://www.wind-power-program.com/turbine_characteristics.htm Yaw system. (2016, May 5). Retrieved from Wikipedia: https://en.wikipedia.org/wiki/Yaw_system

Emerson
Operational Certainty Consulting
1100 Louis Henna Blvd
Round Rock, TX 78681 USA
+1 888 889 9170

www.emerson.com/opcertcon