ELECTRIC POWER RESEARCH INSTITUTE

Assessment of Supervisory Control and Data Acquisition Data Mining for Wind Turbine Condition Monitoring and Performance Improvement

2011 TECHNICAL REPORT

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Abstract

As the wind industry grows and matures, many of the larger wind turbines (2 MW and above) are being outfitted with sophisticated condition-monitoring systems (CMSs), supplied either by the original equipment manufacturer or through a third party to reduce failures, decrease maintenance downtime, and improve reliability. Such systems use vibration sensors in key positions and lubrication oil analysis, with costs of the hardware relatively high, and suffer from spurious alarms. The lifetime cost-benefit ratio of CMSs for large turbines located in remote locations and especially for offshore wind farms is high; however, for wind turbines below 2 MW (>180 GW installed capacity worldwide), the added expense of installing or retrofitting an enhanced CMS is considered in many instances marginally economic. Yet, CMSs can be just as effective for these sub-2 MW turbines as they are for larger models.

All modern utility-scale wind turbines are equipped with supervisory control and data acquisition (SCADA) systems, which are primarily used to operate turbines and collect operating data, such as wind conditions, turbine's power production, turbine's faults, alarms, and downtime. SCADA systems also acquire and record other parameters, which, if properly sampled and mined, can indicate impending component failures.

The SCADA data mining of operational signals can provide a cheap, globally effective condition-monitoring (CM) solution for smaller wind turbines. For large wind turbines, a multiparameter approach based on comparison of independent signals should increase the confidence in fault signal interpretation and alarms generated by the conventional CMS, potentially reducing the risks and costs of false alarms.

In addition to CM application, SCADA systems are being developed to provide cost-effective ways to improve the overall performance of wind turbines and wind farms, which will translate into significant increase in revenues.

Keywords

Asset management
Condition monitoring (CM)
Data mining
Supervisory control and data acquisition (SCADA) system
Wind turbine

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Section 1: Executive Summary

As the wind industry grows and matures, many of the larger wind turbines (2 MW and above) are being outfitted with sophisticated condition monitoring systems (CMS), supplied either by the original equipment manufacturers (OEM), or through a third party, to reduce failures, decrease maintenance downtime, and improve reliability. Such systems use vibration sensors in key positions, and lubrication oil analysis, with costs of the hardware relatively high and suffer from spurious alarms. The lifetime benefit-cost ratio of CMS for large turbines located in remote locations and especially for offshore wind farms is high; however, for wind turbines below 2 MW (>180GW installed capacity worldwide) the added expense of installing or retrofitting an enhanced CMS is considered in many instances marginally economic. Yet, CMS can be just as effective for these sub-2 MW turbines as it is for larger models.

All modern utility scale wind turbines are equipped with supervisory control and data acquisition (SCADA) systems, which are primarily used to operate turbines and collect operating data such as wind conditions, turbines power production, turbines faults, alarms, and down time. SCADA systems also acquire and record other parameters that, if properly sampled and mined, may indicate impending component failures.

The SCADA data mining (SDM) of operational signals may provide a cheap, globally effective condition monitoring (CM) solution for smaller wind turbines. For large wind turbines, a multi-parameter approach based on comparison of independent signals should increase the confidence in fault signal interpretation and alarms generated by the conventional CMS, potentially reducing the risks and costs of false alarms.

In addition to CM application, SCADA systems are being developed to provide cost-effective ways to improve the overall performance of wind turbines and wind farms that will translate into significant increase in revenues.

SDM software models can typically be incorporated into existing enterprise SCADA system architecture as these allow add-ins and third-party algorithm development. Since many data historians are already widely used in the wind industry, SDM should not require any additional hardware, and SDM-based condition-monitoring and performance-monitoring can be offered completely remotely by a third party. Since data-mining algorithms are adaptive, as the turbine population being monitored grows, so will the confidence and predictive power of the application.

In this study, three probabilistic cost benefit analyses were run to show the potential change in cost of energy (CoE) and Net Present Value (NPV) for (1) a 750 kW turbine retrofitted with SDM software and with 15 years of remaining life, (2) a 2.5 MW turbine with conventional CMS and SDM and with 20 years of remaining life, and (3) a 2.5 MW turbine with conventional CMS and SDM and with the potential for extended life (20+ years) as a benefit of SDM. CoE is estimated using the EPRI-TAG method. The Palisade software program, @Risk, was employed to execute a stochastic simulation of the cost model to obtain the uncertainty in the results.

The 750 kW base case turbine was created such that its characteristics are generally representative of a typical 5-8 year old turbine. The 2.5 MW base case turbine was created such that its characteristics are generally representative of a 1-2 year old onshore wind turbine. These characteristics include, amongst others, capital costs, O&M costs, total availability, downtime due to maintenance, capacity factor, etc.

There are a number of benefits of using SDM for the purposes of CM and power performance improvement, four of which were quantified in terms of economics:

1. Increased power performance due to optimization of power curve
2. Increased lifetime energy capture due to longer life, as a result of CM and preventive maintenance approach
3. Reduced O&M costs due to optimized maintenance planning and reduced failure rates
4. Increased turbine availability due to reduced downtime for maintenance, assuming fewer component failures

This report has estimated that an investment in SDM technology appears to have economic merit across all three scenarios evaluated in the study. Although the impacts of SDM may vary from project to project, it is clear that it should be explored as an option for operators trying to achieve high availability and optimal production through the design life of the turbine and beyond.

The value of this technology may be most relevant to projects that no longer have OEM involvement since they are not likely to benefit from OEM driven improvements such as GE's SDA service – offered exclusively as a bundle with their extended service agreements. For these projects, remote CM and performance monitoring could be effectively provided by third-party suppliers of SDM services.

The cost of operating a 24/7 remote monitoring center was estimated to be roughly $1.2MM per year. It is possible to estimate the number of turbines required to fund such an operation. Assuming a 5-year payback period, the range of P90 values estimated for the annual service fee (charged on a per turbine basis) is just under $6,000 for all three scenarios. A remote monitoring center would therefore need at least 200 turbines under contract in order to cover its operational expenses. IRR values for the three scenarios vary from 24% to 35% over the life of the projects, assuming a payback period of five years.

All three scenarios considered apply to onshore applications. However, the benefits of reduced component failures would be even more profitable for offshore wind plants as well as for tall towers because of the higher costs and downtime associated breakdown and the challenges associated with the offshore environment and higher hub heights, respectively.

Section 2: Introduction

Wind Power Overview

Wind power is one of the fastest growing generation resources in the United States (U.S.) and elsewhere in the world. The worldwide potential for new wind project development remains quite large. The industry expects wind to become a significant component of future power generation portfolios, both to reduce dependence on foreign energy sources as well as to reduce greenhouse gas emissions. As of December 2010 the installed wind capacity was over 40 GW in the U.S. and over 195 GW worldwide; and it is forecast to nearly triple to 100 GW and 450 GW by 2014. The industry considers the major wind turbine components to be mature commercial technology. However, failures of gearboxes, blades, electrical controls, and other components continue to impact the reliability and productivity of wind power plants and drive up operations and maintenance (O&M) costs.

As the industry moves forward, the ability to reliably predict and detect component failures in wind turbines, as well as continued efforts to optimize their power performance, will be critical to reducing O&M costs as well as increasing the reliability and profitability of wind turbines and wind plants.

Wind Industry Targets

The remote monitoring and SCADA data mining technologies evaluated in this report are discussed in context with targets for wind turbine technology improvements established by the International Energy Agency (IEA) and the U.S. Department of Energy (DOE). These targets are expected to be achieved over the next several decades. With respect to total investment costs, the IEA in its 2009 Technology Roadmap for Wind Energy [1] assumes a 23% reduction as a result of technology development, deployment, and economies of scale for onshore installations by 2050, and a 38% reduction for offshore installations. The DOE, in its report outlining a path to achieve 20% wind energy by 2030 [2], predicts that reaching that goal will result in a 10% reduction in capital cost for onshore installations, and 12.5% reduction for offshore by 2030. Targets for O&M cost reductions are also established. The IEA report sets a target of 17% reduction in O&M costs by 2030 and 23% by 2050 for onshore installations. For offshore projects IEA predicts a 25% reduction by 2030, and 35% reduction by 2050. The DOE anticipates a reduction in O&M costs of 14% by 2030 onshore and 20% for offshore.

In addition to the IEA and DOE targets, advanced remote monitoring and data mining can also contribute to meeting wind industry availability, failure rate and downtime targets such as those issued by the European Commission's ReliaWind project [3], including:

- Operational availability:
  - Offshore target: 97-98%
  - Onshore target: 98-99%
- Mean Time between Failures (MTBF):
  - Offshore target: 20% increase
  - Onshore target: 10% increase
- Mean Time to Repair (MTTR):
  - Offshore target: 50% reduction
  - Onshore target: 20% reduction

It is worth noting that these ReliaWind targets are based on the European experience. Reviews of U.S. onshore wind project data have shown that North American wind plants have had significantly lower average availability (around 2%-5% lower) [4] but also higher average wind speeds and therefore higher capacity factors as compared to Europe. Therefore a different set of targets may be needed in the U.S. to account for higher loading of turbines.

Improvements in turbine availability over the first few years of operation are largely expected to be driven by factors relating to turbine design, technology, and site conditions. However, advances in fault detection, performance optimization, and maintenance of wind plants can have a significant impact on reducing O&M costs and turbine downtime, especially later in the project lifecycle when large part failures with high replacement costs and long downtimes become more frequent.

Wind Turbine Maintenance Costs

Wind project maintenance can be separated into two categories (scheduled and unscheduled maintenance) as well as two time periods (warranty and post-warranty periods). During the warranty period (typically 2 to 5 years), turbine maintenance is typically covered by a manufacturer's warranty. EPRI's 2009 Technical Assessment Guide (TAG) presents O&M cost estimates for three representative utility-scale wind plants with rated capacities of 50, 200, and 500 MW [5]. As with capital costs, larger projects typically experience economies of scale with O&M costs. The $/kW-year O&M costs of the 50 MW project are 10% higher than those of the 200 MW project; those of the 500 MW project are 5% lower than those of a 200 MW project. Figure 2-1 shows the annual O&M costs over a 20-year project life for a representative 200 MW wind plant. Immediately after the initial warranty period (here assumed to be 2 years), turbine O&M costs typically are lower than the warranty costs but are then expected to double over the life of the project which reflects increasing wear on the turbine and a greater probability of part failures.

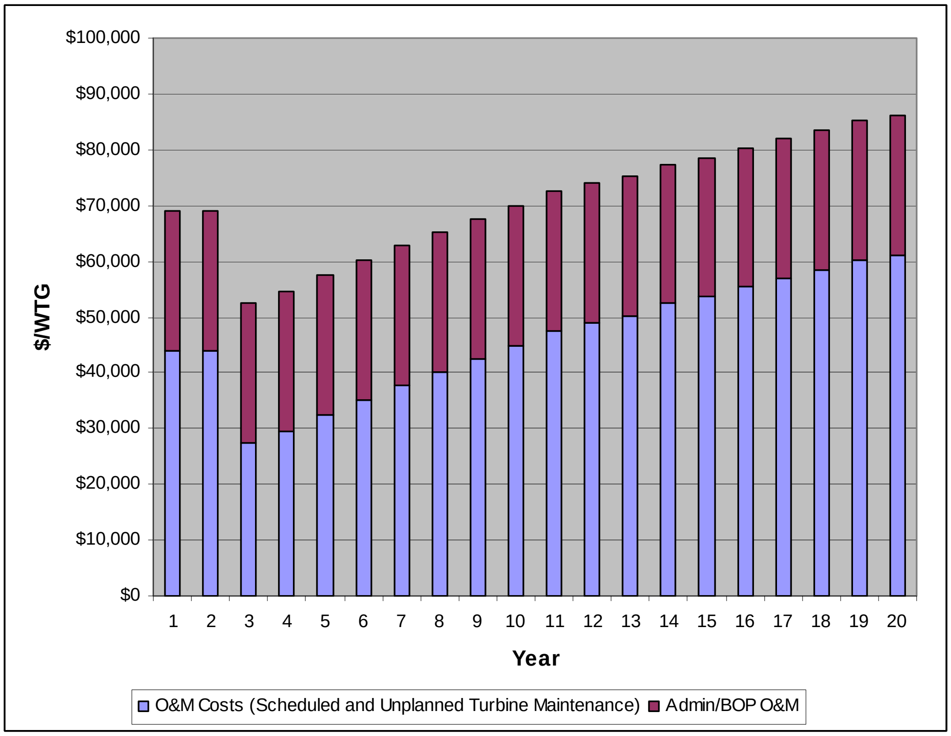
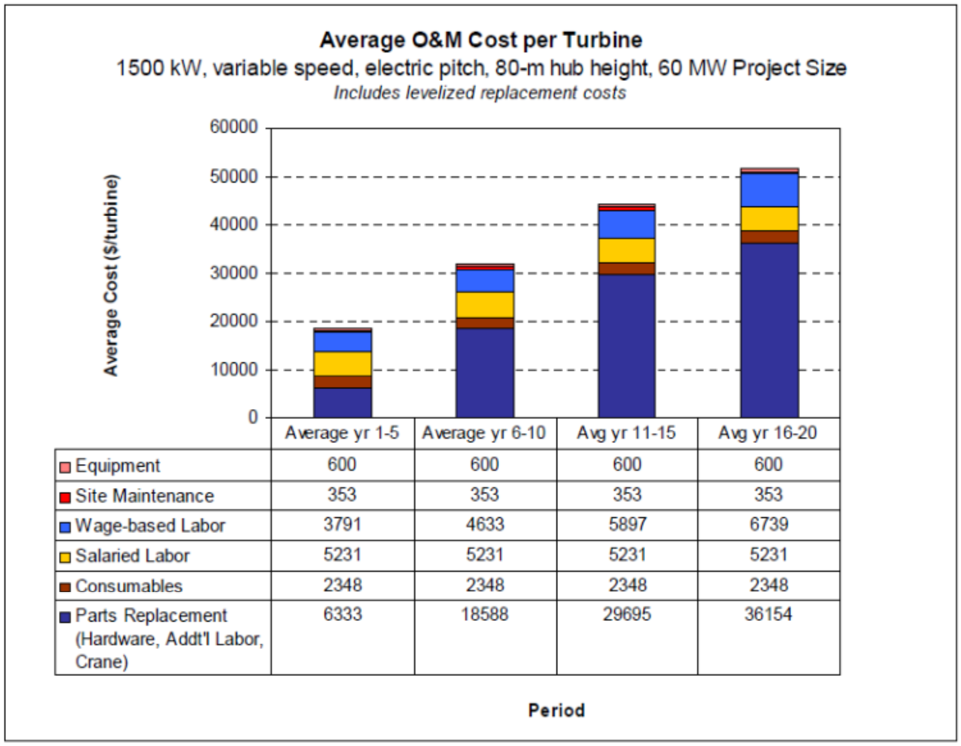


Figure 2-1
Estimated Operations and Maintenance Costs per Turbine for a 200 MW Wind Project (December 2009 $)

A 2008 National Renewable Energy Laboratory (NREL) report presents the results of an O&M cost model development for commercial wind turbine generator (WTG) facilities [6]. Data for this project were taken from a variety of sources, including manufacturer publications, published case studies, expenditures and service logs from operating wind farms, and conversations and interviews with project managers and technicians.

The O&M model results show total costs associated with scheduled maintenance, unscheduled maintenance, and levelized replacement costs (LRC). The last category is commonly used to estimate reserves that will be required for major component overhauls or replacements.

The O&M cost estimates in this study demonstrate that the major contributor to overall O&M costs over the project life is parts replacement, followed by labor costs. Figure 2-2 shows that in the first 5 years, parts costs are estimated to be 30% of the total cost, and by the end of the project life, they exceed 65% of the total cost.



	Average yr 1-5	Average yr 6-10	Avg yr 11-15	Avg yr 16-20
Equipment	600	600	600	600
Site Maintenance	353	353	353	353
Wage-based Labor	3791	4633	5897	6739
Salaried Labor	5231	5231	5231	5231
Consumables	2348	2348	2348	2348
Parts Replacement (Hardware, Addt'l Labor, Crane)	6333	18588	29695	36154

Figure 2-2
O&M Costs per Turbine, 5-Year Averages [3]

The O&M cost data shown in Figure 2-2 highlight the impact that unplanned failures leading to unscheduled maintenance and replacement of parts can have on project maintenance costs over the life of the project. In a further examination of this potential cost impact, the NREL study found that for a generic 1.5 MW, variable speed, electric pitch WTG with an 80-m hub height, parts replacement costs are dominated by replacement of large parts that require the use of a crane (Figure 2-3 and Figure 2-4).

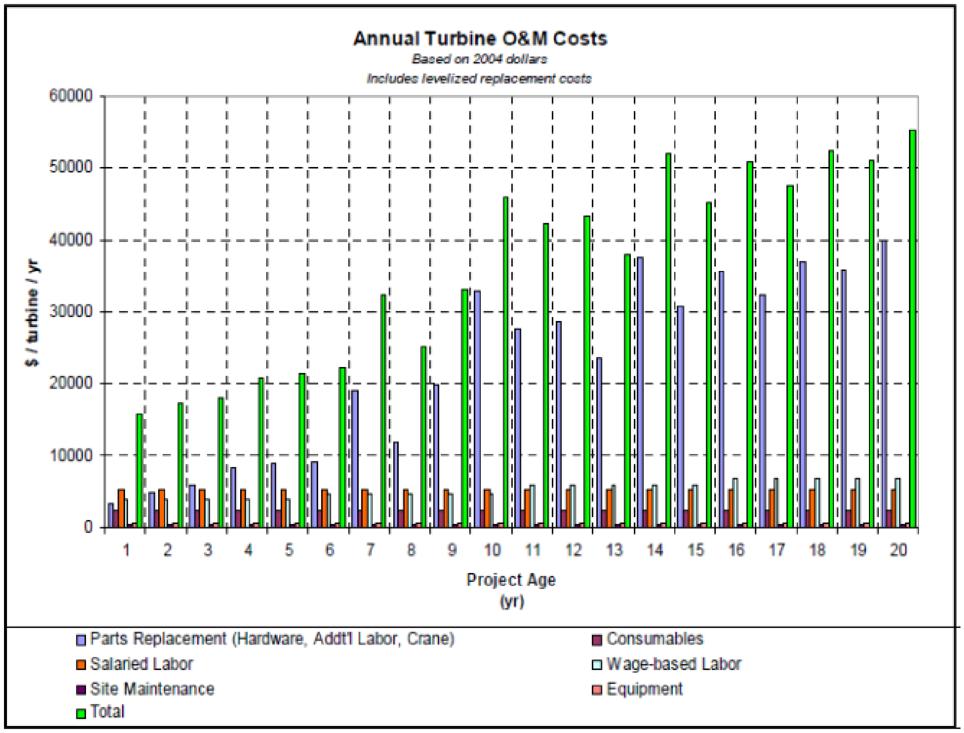


Figure 2-3
Annual Turbine O&M Costs [3]

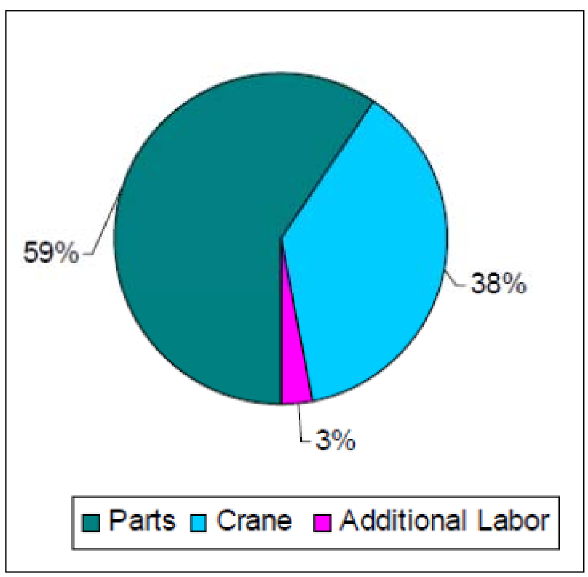


Figure 2-4
Parts Replacement Cost Breakdown [3]

A closer examination of parts replacement costs reveals where the highest costs are incurred. The NREL study reports that the gearbox (including lubrication), the rotor system (including blades) and the generator make up the largest cost drivers (Figure 2-5).

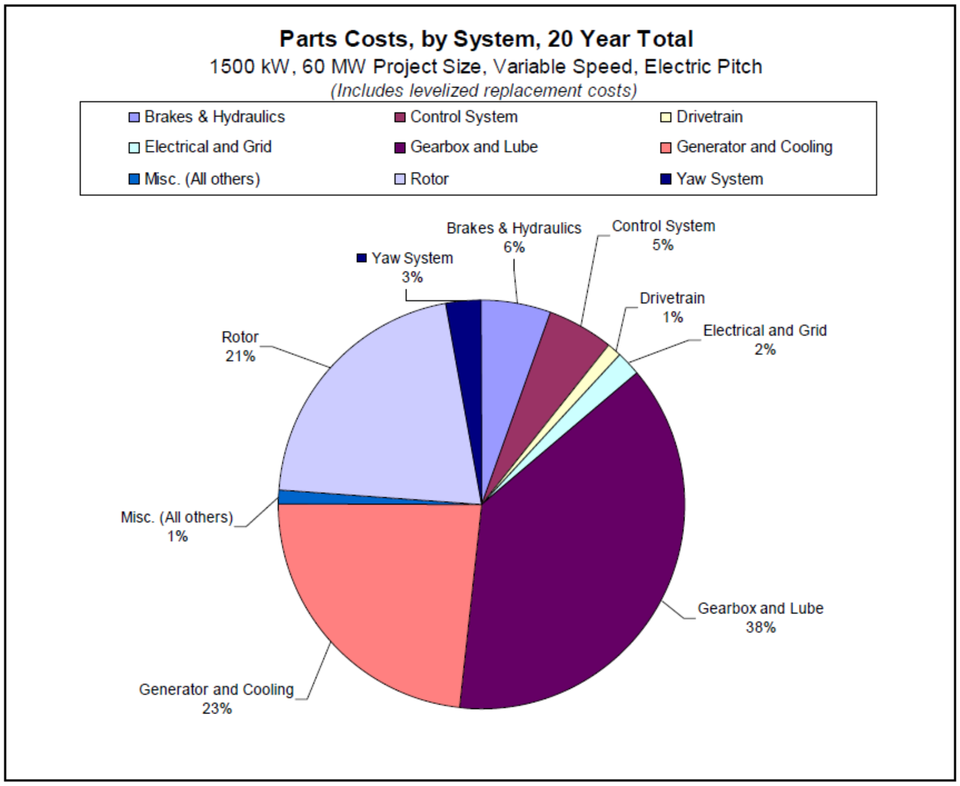


Figure 2-5
Parts Costs Over 20-Year Project Life, by System [3]

Wind Turbine Availability and Component Failure Rates

A recent study by the Fraunhofer Institute for Wind Energy and Energy System Technology (IWES) [7] concludes that wind turbines experience on average about one week of downtime every year due to unscheduled failures. Approximately 35% of that downtime is caused by failures to drive train components (gearbox), 24% is caused by structural failures (mainly blades), and 41% by electrical component failure (namely the generator and power electronics). These results are presented in more detail in Figure 2-6 below.

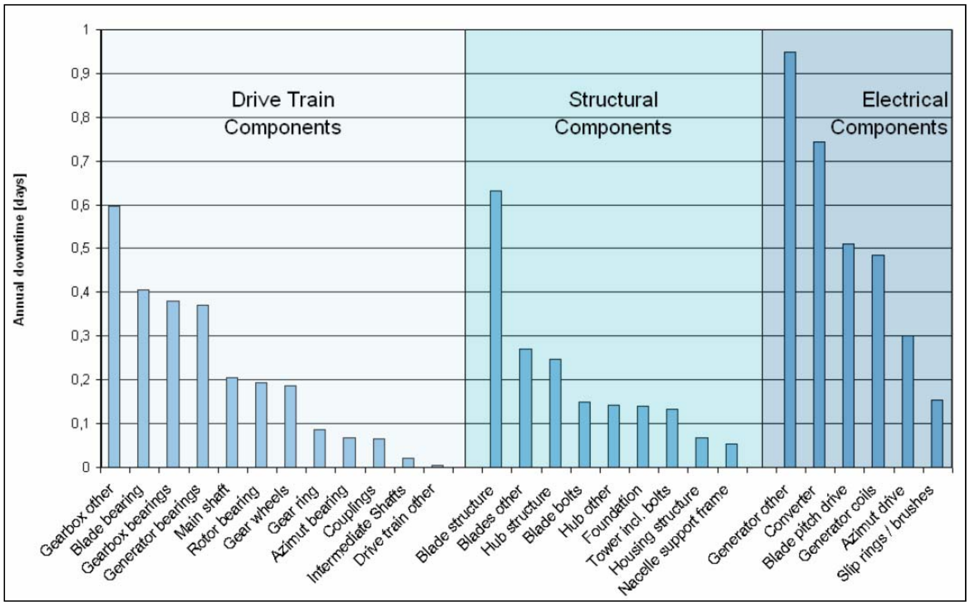


Figure 2-6
Annual Downtime – Contributions by Sub-Assemblies [6]

Overall, wind turbine availability is generally considered to average approximately 95% to 97% with industry estimates ranging from 93% [4] to 99% [7]. It is commonly accepted that WTG availability of 97% can be expected in the first few years of operation. However, as wind turbines age, failure rates of components such as blades, gearboxes, and generators increase. Since the repair and replacement of these large parts are typically accompanied by significant downtime, turbine availability of 97% should not be expected in the second decade of a wind plant operation without adequately accounting for increased efforts in preventive maintenance including turbine health monitoring as well as developing cost-effective methods for predicting and detecting component failures.

Conventional Condition Monitoring Systems

The CMS currently used by the wind industry were imported from other rotating machine power generation industries (mostly combustion turbines) where the technology has been successfully applied for many years. However, wind turbines differ from these machines in that they rotate at a slower speed and have rapidly varying torque and as a result CMS technology such as vibration, temperature, and oil analysis have not proven as effective in wind as they have in other industries. These techniques are also not ideally suited for detecting and monitoring all wind turbine fault and failure types. For instance, lubrication oil analysis is proving capable of detecting gearbox tooth failures but cannot detect failures outside the gearbox. Vibration monitoring instrumentation is also limited in what mechanical failures it can detect. Finally, none of these systems are geared towards detecting electrical faults which, as mentioned earlier, account for a majority of wind turbine faults. For these reasons, a SCADA data mining approach based on monitoring the wind turbine power output signal could provide an inexpensive, globally effective CM solution for smaller wind turbines as well as for larger turbines which may not have CMS installed. This technology could also be used to increase the confidence in fault signal interpretation and alarms generated by the conventional CMS for large wind turbines where those systems are installed, potentially reducing the risks and costs of false alarms.

Section 3: SCADA Data Mining Technology Review

Overview

SCADA data mining (SDM) was formally established as a field of science in the mid-1990s with the first applications being in the combustion turbine and aerospace sectors. Today, it is generally considered a mature and versatile technology capable of modeling and analyzing almost any process. In the wind industry this technology is still relatively new and is being explored primarily by academia (universities and research institutes) and some of the larger OEMs such as Vestas and General Electric (GE).

Today's wind turbine CMS require the installation of vibration sensors in key positions and lubrication oil analysis systems, with relatively high hardware costs. The average cost of installing CMS instrumentation on a turbine is approximately $10,000 but can vary depending on system complexity and capability. The lifetime benefit-cost ratio of CMS for large turbines located in remote locations, and especially for offshore wind farms, is high. This is due to the increased time and cost of mobilizing and transporting parts and labor in a remote location. Not only is the repair work more expensive but failures in remote locations often have longer MTTR resulting in longer downtimes and lower project revenue. Being able to better detect, track and possibly even predict component failures give these projects the ability to better coordinate maintenance activities so that costs and downtimes can be minimized. However, for smaller machines (<2 MW rating) especially those that have been in operation for a few years, the added expense of retrofitting a CMS is considered, in many instances, marginally economical. Yet CM can be just as important for these sub-2 MW turbines as it is for larger models. The market for these machines is significant with an estimated 25 GW installed capacity in the U.S. and 180 GW worldwide.

All utility scale wind turbines are equipped with SCADA systems, which are primarily used to operate turbines and collect operating data such as wind conditions, turbine power production, turbine faults, alarms and down time. SCADA systems also acquire and record other parameters that, if properly sampled and mined, may indicate impending component failures. This section provides an overview of the current state of the technology needed to perform SDM on modern wind turbines with a particular focus on mining and analyzing data from the three-phase total power output signal.

SCADA System Technology Review

Multiple types of SCADA systems are available for wind project owners and operators, each with their own advantages and disadvantages. In very general terms, these SCADA systems can be grouped into two broad categories: those offered by the turbine manufacturers, and those offered as third-party systems. This section outlines typical characteristics associated with OEM SCADA and third-party SCADA systems both of which have a role to play in the development of SDM technology.

OEM SCADA Systems

Individual utility scale projects almost always utilize the SCADA system provided by the turbine manufacturer as this is a prerequisite of turbine warranty agreements. These SCADA systems typically have the capacity to display data in tabular and graphical format. Available displays normally include an overall layout of the project with indicators for the status of each turbine, meteorological conditions, indicators for aggregate power output, total delivered MW-hours, and event and alarm logs. Often the user can access information at the individual turbine level such as temperature of the gearbox or pitch position. Figure 3-1 shows a screen shot from Vestas' SCADA system detailing real-time performance data on a single turbine.

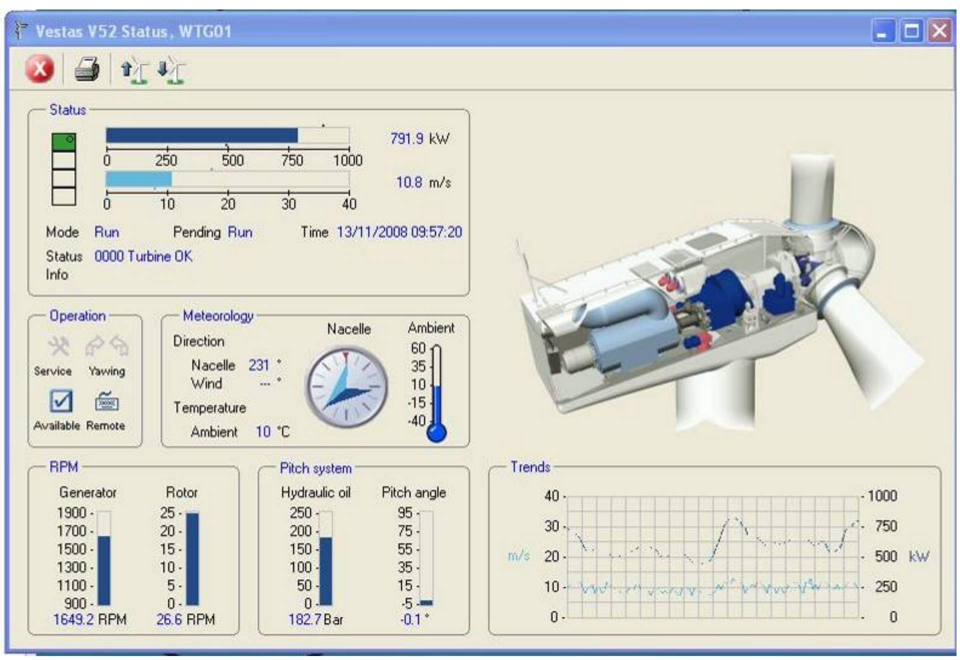


Figure 3-1
Example Screen Shot of Manufacturer SCADA Display (from Vestas)

The OEM SCADA systems are optimized to support real-time project O&M. Turbine manufacturers' SCADA systems are generally very good at performing the day-to-day tasks of running a wind farm: safely starting and stopping turbines, providing details on the current state of all of the turbines and what faults or other problems are present, and other routine tasks. Because the OEM SCADA may be more deeply integrated into turbine operations than third-party systems, it may not be possible to easily access all functionality of the turbines without using the OEM SCADA. A wind turbine SDM system would therefore require access to the OEM SCADA in order to extract real-time energy output data.

Wind turbine controllers update at a rate around 20 Hz, but OEM SCADA systems usually poll the data at a much slower rate, on the order of seconds. Historical data – such as wind speed and power output – are stored as the 10-minute average, minimum, maximum, and standard deviation over a specified period (e.g., daily, monthly, annual periods). However, many OEM systems can also log events such as turbine faults independently of the 10-minute data. Although some systems allow storage of selected parameters at a higher rate most OEM systems will only allow project owners to access the averaged data. Figure 3-2 shows an example of the level of data mining possible using only an OEM SCADA system. In this example, Siemens' Wind Power Supervisor (WPS) system shows a plot of 2 months of historical data for gearbox bearing temperature, generator revolutions per minute (RPM) as well as internal and internal temperature readings.

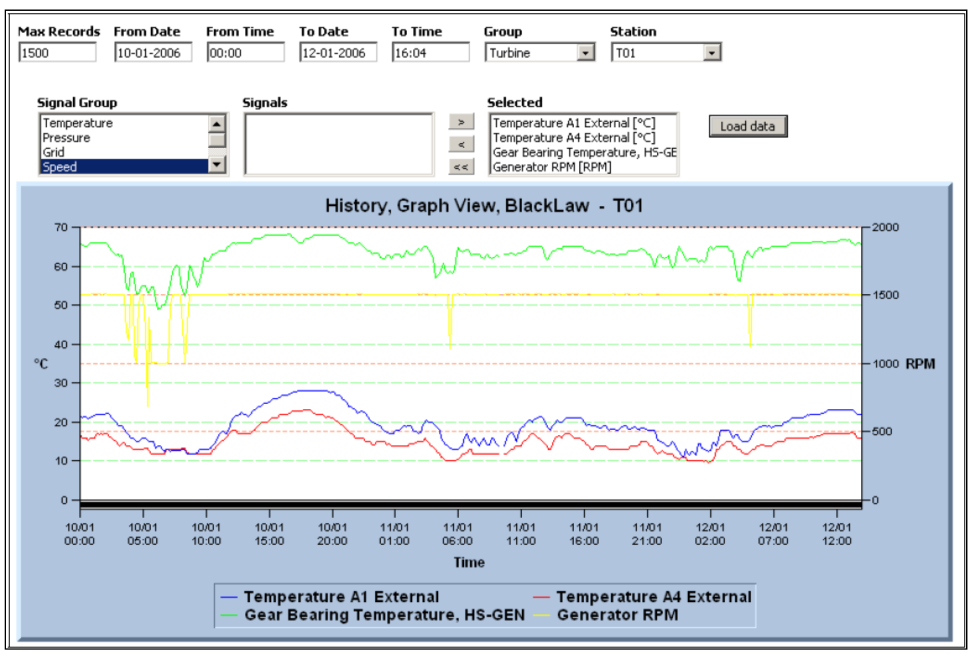


Figure 3-2
Plot of Historical Data from Siemens Web Wind Power Supervisor SCADA System

Third-Party SCADA

Because of the limitations of OEM-provided SCADA systems, some owners are supplementing, and in some cases replacing, these systems with third-party SCADA options. A single company may own and/or operate multiple wind farms, which may run different turbine types and SCADA systems. In this case it is typical to connect the wind farms to a control center. The central SCADA system can communicate with the various wind farm nodes using OPC (open connectivity) or some other industry standard communication protocol to track and display real-time wind and performance data.

In addition, owner/operators with large WTG fleets from different manufacturers may elect to invest in third-party enterprise-scale SCADA or other data collection systems. A number of vendors provide enterprise SCADA systems to the wind industry; one of the most widely-used systems is PI (from OSIsoft) which was being applied by 13 of the top 15 wind plant operators worldwide as of late 2008.

A third-party SCADA system can either run in parallel with manufacturer SCADA as an enterprise data system or in place of the OEM system as a third-party SCADA. These systems can support and complement SDM technology in several ways:

- **Third-party systems often provide better data storage and analysis tools.** Although often not as well-suited for real-time site operations as OEM SCADA systems, third-party systems will generally offer more options for analysis of project operations. Some first-party SCADA systems use database engines with limited capacities. As a result, projects with large number of turbines may need to archive and delete project data on a regular basis, sometimes as often as monthly. This makes analysis of longer periods of data difficult and time-consuming. Third-party enterprise-scale systems can remove this limitation and facilitate the mining and analysis of large amounts of archived data. This would allow an SDM system to use algorithm-based pattern-recognition software to analyze trends of turbine power performance or faults over long time periods.
- **Third-party systems are often programmable and flexible.** The ability to produce customized views, reports, analysis tools, and data products allows users to make third-party SCADA systems do almost anything they want, within the constraints of the data being gathered and the time and effort required for the programming. While this effort can be significant in some cases, most systems provide relatively user-friendly tools that allow for the creation of fairly powerful reports and analyses without requiring extensive knowledge or training. Much of the academic research being done on SDM for wind turbines has made use of existing third-party SCADA platforms such as PI which allow the user to program algorithms for mining and analyzing archived data.

- **Many different turbine types and other equipment can be integrated into a single third-party SCADA system.** While OEM systems will only allow an owner or operator to work with that turbine manufacturer's machines (and in some cases only a limited subset of turbine models) and a few, pre-defined other devices such as project meteorological towers, there are no limitations on the types of systems that can be combined in a third-party enterprise-scale system. For owners/operators who operate multiple projects with many different turbine models – or if multiple turbine models are present at the same project – being able to combine data across all of these turbines can be essential to the successful application of SDM technology.
- **Integration with other measurement devices.** Wind projects may have many measurement devices other than the turbines, including meteorological towers, substation meters, and CMS. Many OEM systems have limited flexibility to incorporate data from these systems, while most third-party enterprise SCADA systems can be customized to include all project data.
- **Integration with CMS.** Large owners and operators are increasingly using enterprise SCADA data systems to incorporate some aspects of CMS. The SCADA data from entire fleets are being transmitted to remote monitoring centers, where the operations of individual wind plants and wind turbines is being analyzed and diagnosed. The trending of various parameters, such as bearing temperatures and drive train vibration, is used to identify major components that require inspection and possibly maintenance. The consolidation of the SCADA data and operational analyses at remote monitoring centers allows resources, including tools and expertise, to be shared by multiple projects. The same could be done for data mining of the electric power output signal of each wind turbine within an owner or operator's portfolio. A third-party SCADA system could consolidate data streams from several OEM SCADA systems allowing for remote monitoring of numerous projects without the need for typical CM instrumentation. IEC 61400-25 is an international standard that addresses the issue of proprietary communication systems across OEMs by providing uniform information exchange for monitoring and control of wind turbines. This standard is intended to improve interoperability and enhance the capacity to link machines of different makes using a single third-party system. Several OEMs have developed, or are in the process of developing, IEC 61400-25-compliant interfaces to improve the operational management of wind plants with turbines and sensors from various manufacturers. One example is Repower's REguard Interface B IEC 61400-25 which can be directly integrated into control systems of operational wind turbines.

Examples of third-party SCADA systems are listed below and include systems developed by renewable energy consultancies, software developers, electrical equipment providers and wind turbine operating companies [19].

- GH SCADA and SgurrTREND are developed by renewable energy consultancies in collaboration with wind turbine manufacturers, wind farm operators, developers and financiers to meet the needs of all those involved in wind farm operation, analysis, and reporting.
- CONCERTO developed by AVL is not specialized for SCADA data analysis. It is a generic data post processing tool focusing on quick and intuitive signal analysis, validation, correlation and reporting for any kind of acquired data.
- SIMAP is based on artificial intelligence techniques. The new and positive aspects of this predictive maintenance methodology have been tested on wind turbines. SIMAP has been applied to a wind farm owned by a Spanish Wind Energy Company called Molinos del Ebro, S.A.
- INGESYS Wind IT was developed by IngeTeam, an electrical equipment provider. The system aims to integrate wind power plants into a single system and then optimize wind-farm management. INGENSYS Wind IT also provides an advanced reporting service for power curve analysis, faults, alarms, and customer reports.
- Gateway System is developed by another electrical equipment provider called Mita-Teknik. It is a PC-based software package, designed to collect, handle, analyze and illustrate the data from the Wind Turbine Controller with simple graphics and text.
- Other products such as BaxEnergy WindPower Dashboard (BaxEnergy GmbH), CitectSCADA (Schneider Electric), ICONICS for Renewable Energy (ICONICS Inc), InduSoft Wind Power (InduSoft), reSCADA (Kinetic Automation), WindCapture (SCADA Solutions), Wind Systems (SmartSignal), MATRIKON's Wind Asset Monitoring Solution, Cosworth's PI Diablo system, and Emerson's Ovation SCADA platform are integrated SCADA systems all developed by industrial software companies, which aim to provide reliable, flexible and high performance applications for wind turbine automation, monitoring and control.

In summary, the ability to analyze project performance, monitor turbine health, and improve operations depends on the data that have been recorded from the project. Data mining can perform real-time data processing when integrated with an OEM SCADA system as well as long-term trending of data from various projects and a diversity of turbine models when coupled to a modern third-party SCADA system. This report will detail how both of these functionalities can add to the effectiveness of SDM.

Basic Principles of SCADA Data Mining

The general process for performing SDM on any machine or process, including wind turbines, can be summarized as follows:

1. **Acquire Data**. Data should be at highest sampling rate that computing power can handle but for practical purposes it should also be at the lowest rate needed to solve the problem.
2. **Screen Data**. What are the key parameters needed to solve the problem? Once identified those key parameters should be isolated from the data stream.
3. **Develop Model**. Once the key parameters have been isolated an algorithm (or model) can be created to analyze the data stream for that parameter. This can be in the form of pattern-recognition software or a model looking for specific pre-defined threshold values.
4. **Validate Model**. The model must be validated against empirical data (that is, the model should be run on historical data where the outcome is already known in order to assess its capacity to predict a specific outcome on an operational turbine).
5. **Generate Product**. Once the model has been validated, a product can be created (and marketed) for a specific application (for example, remote monitoring and fault-detection of wind turbines).

Ideally, the following data are required for developing the algorithms needed to mine and analyze wind turbine power signals:

- Full range of power output data.
- Data on all faults (including rare faults).
- Power data immediately prior to a failure, as well as power data during a failure, are needed to develop predictive algorithms.

One year of SCADA data would provide sufficient input for a developer to produce an SDM model for the specific turbine model from which the data are drawn.

The application of SDM technology to wind turbines is typically focused on achieving one of the following: improving power performance or providing condition monitoring.

Power performance can be optimized through data mining by analyzing each individual turbine's power output data in order to build machine-specific power curves. These power curves can then be used to identify underperformance issues, optimize performance and improve forecasting. SDM can also be used for the purposes of condition monitoring and improving reliability as it has shown a strong capacity for predicting and detecting impending turbine faults (both electrical and mechanical). Using SDM to predict potential failures allows for better planning of repair activities and can help prevent a minor fault from turning into a major (and much more costly) failure. These two applications of SDM and the potential benefits they provide are discussed in detail in Chapter 4.

Performance optimization is perhaps the more difficult application of data mining since it involves a 2-way transfer of information. In order to improve power performance one needs to be able to optimize wind turbine controls. This requires higher frequency data (on the order of 10 seconds) which typically means having access to OEM protocols or the actual OEM SCADA data stream. On the other hand, data mining for the purposes of CM requires only a one-way flow of data and can often be achieved with lower-frequency data – such as typical 10-minute data provided to project owners by the OEMs.

SCADA Data Mining – Academic Research

Universities and research bodies across the U.S., Europe, and Asia are actively involved in the development and testing of SDM technology for application in the wind industry and include institutions such as the University of Iowa (Iowa City, U.S.), Durham University (Durham, UK), University of Manchester (Manchester, UK) and Seoul National University (Seoul, Republic of Korea).

The following section provides an overview of a representative sub-set of the SDM research being conducted at these academic institutions with the objective of improving remote monitoring, fault detection, and power performance improvement of wind turbines and is based on the available published literature.

"Dynamic Control of Wind Turbines" [8] and "Adaptive Control of a Wind Turbine with Data Mining and Swarm Intelligence" [11]

Dr. Andrew Kusiak of the University of Iowa, along with Zijun Zhang, Wenyan Li, and Zhe Song, has investigated a data-mining approach to building adaptive control algorithms that would optimize the power production and minimize the turbine loads, characterized for a specific turbine after a period of machine learning. This section looks at the results published in two articles [8][11] and the master's thesis of Wenyan Li [18].

In the article "Dynamic control of wind turbines"[8] from the 2009 issue of the journal Renewable Energy, written with Li and Song, a dynamic algorithm for controlling a wind turbine in order to optimize turbine performance is presented. Specifically, the algorithm seeks to meet the following criteria: maximize the active power output and minimize the rate of change in the power output, the rate of change in the rotor speed, the rate of change in the generator torque, and the rate of change in the pitch angle of the blades.

The input variables used to weigh these objectives are the 10-second wind speed, the turbulence intensity (calculated from the standard deviation of the preceding six 10-second wind speed values), and the current level of power demand. In this case, power demand was a simulated signal, but it may be roughly knowable in practice. Eight scenarios were simulated: high and low wind speed, high and low turbulence intensity, and high and low power demand. Weights for each scenario were picked by hand. The algorithm used real data to build the relationships, and then simulated optimal controls for those wind conditions for both low- and high-demand scenarios. This process seems robust and could be useful if possible to implement.

In addition to revisiting this adaptive control algorithm in Chapter 5, Li's thesis "Predictive Engineering in Wind Energy: a Data-Mining Approach" [18] has a section in Chapter 3 describing the creation of a generalized model of the wind turbine being studied using data from 10 random-selected turbines. 10-second data were analyzed looking at power output, generator torque, generator speed, wind speed, bearing temperature, pitch angle, nacelle position, and rotor speed. Models for estimating power output *(y1)* and rotor speed *(y2)* were developed as functions of wind speed *(v)* and of the controllable parameters blade pitch angle *(x1)* and generator torque *(x2)*. It evaluates the computational models Boosting Tree and Neural Network and the impact of including past states.

The article "Adaptive Control of a Wind Turbine with Data Mining and Swarm Intelligence" [11] by Kusiak and Zhang was published for the IEEE Transaction on Sustainable Energy. The approach used in this paper was similar to that in [8], in using data mining to optimize controls based on current conditions (specifically, wind speed, generator torque, blade pitch angle, and power generated).

This article focused on two of the five criteria of the other approach: maximize the power production and minimize the torque ramp rate (the change of generator torque with respect to time). Limits were set to prevent a change in the pitch angle by more than 2° up or down and the torque by more than 20% of the maximum torque. Absolute limits were set on the blade angle of -0.57° and 90.61°.

Neural network models were used to create the power production predictions and a particle swarm fuzzy algorithm was used to weight the two objectives. The power production is predicted based on the previous five 10-second samples and the power demand is generated from a normal distribution with mean demand based on time of day.

In order to operate as adaptive controls of a turbine, the calculation must use 10-second sampling to predict and modify the torque and pitch angle in order to make changes in time. This methodology was able to calculate the new control values in 3 seconds.

“Analysis of Wind Turbine Vibrations Based on SCADA Data” [9]

Kusiak’s group also has worked on approaches to predict turbine faults before they occur.

“Analysis of Wind Turbine Vibrations Based on SCADA Data” [9] was written by Kusiak and Zhang and was published in the Journal of Solar Energy Engineering in August 2010. This article looks at characterizing the signature of increased vibrations (as drive train acceleration or tower acceleration) based on other external or controllable parameters (generator torque, pitch angle, and wind speed).

The paper also looked at vibration data in the frequency domain in addition to the time domain, in order to observe any resonant frequencies caused by power train malfunctions, but given the low sampling rate of 0.1 Hz, no conclusive information was gained from this process.

The model performed quite well at predicting the drive train acceleration and tower acceleration (about 97% and 93% accuracy respectively). It is not clear if or how this technique could be used in condition monitoring, but it appears that it could be used to determine the impact of controls on measured vibrations and taking that into account in building methods for turbine controls.

“A Data-Driven Approach for Monitoring Blade Pitch Faults in Wind Turbines” [12]

Andrew Kusiak and Anoop Verma present a prediction model that aims to identify blade pitch faults ahead of time (using data sampled at 5-second periods) in the IEEE Transaction on Sustainable Energy. Faults caused by blade angle asymmetry (pitch angle at the three blades are not the same) and blade angle implausibility (pitch angle setpoint and the actual measured pitch angle diverge) were analyzed by using, six different measures derived from SCADA data. Blade angle deviation from its own setpoint (for all three blades) and the blade angle deviation from the other two blades (for all three pairs of blades) along with tower deflection, nacelle revolution, and rotor speed, were used to generate Genetic Programming models where the computer model learns empirically which parameter signatures tend to indicate impending faults, in periods of 5 seconds to 10 minutes before a fault. The authors claim accuracy in the range of 69% to 87% as the time interval decreases. Although the results are promising, the paper did not provide an estimate of the calculation time required to make the prediction or suggestions for adaptive controls to prevent the occurrence of faults once they have been predicted.

“The Prediction and Diagnosis of Wind Turbine Faults” [10]

Andrew Kusiak and Wenyan Li contributed this article to the 2010 issue of the journal Renewable Energy, and Li revisits this subject in Chapter 6 of his thesis [18]. The approach uses the status/fault alarm log along with 5-minute averages of wind, energy, vibration, and temperature parameters, but builds the model to predict faults at three levels based on only wind speed and power output at time (t - n) as the model input parameters. Data sampling was used to create data sets evenly split between timestamps with and without faults or status events. Three levels of prediction were modeled.

For Level 1, predicting whether or not a fault or status of any kind will occur at time t, a Neural Network Ensemble (NN-ensemble) approach was used by building thirty NNs and the best five were selected, with an accuracy of 75% (the rate of correct predictions), a sensitivity of 84% (the ratio of true fault events to predicted fault events), and a specificity of 66% (the ratio of true normal events to predicted normal events). The model was able to continue this level of prediction up to timestamp *t - 9* or 45 minutes beforehand.

For Level 2, prediction of the fault or status category (Categories 1 to 4 or Normal, with the lowest number being most severe), a Standard Classification and Regression Tree (CART) algorithm was used, as it had over 95% accuracy for Normal and Category 4 statuses and had over 50% accuracy for Category 1 to 3 faults. Other methods attempted were unable to predict all three categories of faults. These levels of accuracy roughly stayed the same up to timestamp *t -12* or 1 hour before.

For Level 3, predicting a specific fault event, in this case using status code 296 “malfunction of diverter” (the most frequent status code at Turbine 4), a Boosting Tree Algorithm (BTA) was used, resulting in an accuracy of 70%, a sensitivity of 87%, and a specificity of 63%. This sensitivity stayed relatively high (above 2/3) up to timestamp *t -6* or 30 minutes beforehand.

This approach continues to look very promising, though a couple of areas need further investigation or explanation:

- An investigation of a Level between 1 and 2, looking at the ability to predict any fault in Category 1 to 3 versus a Normal or Category 4 status. This is because Category 4 is events that are either completely benign or caused by human-intervention, a condition that would not be visible in the data. This would be a more consequential version of Level 1 and would likely not appear to be as sensitive to predicting faults as the version presented.
- Which faults can be avoided? To make this prediction algorithm truly useful, analysis would need to be done on a fault code that is both severe and preventable. How long do the calculations take relative to the time available for action?

“Research on a Simple, Cheap but Globally Effective Condition Monitoring Technique for Wind Turbines” [13]

This article (by Wenxin Tang, P.J Tavner, and C.J. Crabtree of Durham University and Michael Wilkinson of Garrad Hassan) looks at time series data on generator torque, rotor speed, and power output to identify signatures in the frequency domain of mechanical or electrical faults. The authors used two small test rigs designed to emulate the essential features of the wind turbine generator, using both a synchronous generator and an induction generator. These test rigs were used in many of the experiments discussed below.

The paper demonstrates the results of a physical rotor mass imbalance using the synchronous generator as well as of an electrical phase imbalance using the induction generator. The signals shown are quite subtle (especially in the first case), but the results to seem to provide useful information for the purposes of fault detection in wind turbines.

"Cost Effective Condition Monitoring for Wind Turbines" [14]

As wind turbines increase in size and machines are placed in more remote locations (e.g., offshore) cost-effective wind turbine CM will have increasingly more importance. This paper by Yang, Tavner, Crabtree, and Wilkinson describes a wind turbine CM technique that uses an algorithm to analyze the generator output power signal and rotational speed for the purposes of fault detection. While conventional CM techniques, such as vibration, lubrication oil, and generator current signal analysis, require the deployment of a variety of sensors and computationally intensive analysis techniques, the detection algorithm presented in this paper uses an adaptive filter to track the energy in prescribed time-varying fault-related frequency bands within the power signal. The central frequency of the filter is controlled by the generator speed, and the filter bandwidth is adapted to the speed fluctuation. Using this technique, both mechanical and electrical fault features can be extracted, with low calculation times, from direct or indirect-drive fixed- or variable-speed wind turbines.

The proposed technique has been validated experimentally by the authors on a wind turbine drive train test rig. A synchronous generator was successively installed on the test rig, and both mechanical and electrical fault like perturbations were successfully detected when applied to the test rig.

"Wind Turbine Condition Monitoring and Fault Diagnosis using Wavelet Transforms" [15]

Some large wind turbines use a synchronous generator directly coupled to the turbine. This paper by Yang and Tavner considers CM and diagnosis of mechanical and electrical faults in such a variable speed machine. The application of wavelet transforms is investigated because of the disadvantages of conventional spectral techniques in processing instantaneous turbine signals. In order to further simplify and reduce the cost of wind turbine CM and fault diagnosis, this paper proposes a new CM technique which removes the negative influence of variable wind in machine CM and investigates the possibility of detecting wind turbine mechanical faults by analysis of the power signal. The effectiveness of the technique is validated by the successful detection of generator winding and rotor imbalance faults on a test rig.

“Condition Monitoring of a Wind Turbine DFIG by Current or Power Analysis” [16]

As wind energy assumes greater importance in remote and offshore locations, effective and reliable CM techniques are required. This paper by Crabtree, Djurovic, Tavner and Smith proposes a method for analyzing electrical signals from the stator terminals of the wound rotor induction generators commonly used in wind turbines. Analytical equations were derived for the frequency content of line current and total instantaneous power for healthy and faulty wound rotor induction generators and these equations were used to analyze signals from test rigs in the steady state. Analysis at constant speed yielded a set of equation constants which describe the frequencies of highest interest as observed from the test rig environments. Once a consistent group of fault frequencies was discovered the data were then demonstrated at variable speed to show the variability of those fault frequencies with speed. The paper concludes that tracking these speed-dependent fault frequencies can be an effective way to monitor the health of a wound rotor induction generator in a wind turbine.

“Condition Monitoring of the Power Output of Wind Turbine Generators Using Wavelets” [17]

This paper by Watson, Xiang, Yang, Tavner and Crabtree looked at monitoring the power output of a variable-speed wind turbine generator and processing the data using a wavelet transform in order to extract the strength of particular frequency components that are characteristic of faults. This was done for doubly fed induction generators (DFIG), commonly used in modern variable-speed wind turbines. The technique was first validated on a test rig under controlled fault conditions and then applied to two operational wind turbine DFIGs where generator shaft misalignment was detected. For one of these turbines, the technique detected a problem 3 months before a bearing failure was recorded. Wavelet transforms were successfully used for the purposes of CM, and the paper suggests that additional data logging at a frequency of approximately 30 Hz would likely be needed in addition to the more traditional 10-minute SCADA data currently logged at most wind power sites. However, the technique described in the paper is significant in that it could be applied to any variable-speed wind turbine using an induction generator and would require very little additional instrumentation beyond a standard OEM SCADA system.

Commercialization and Operational Experience

Data mining has seen most of its industrial development occur in complex, capital-intensive industries (such as oil and gas, chemical, steel, paper, aerospace, and the military) as well as high-value, long service-life product manufacturers facing a pressing demand to minimize unplanned maintenance and achieve higher asset uptime. In these industries mature SDM have been developed with the purpose of improving logistics, predicting failures and minimizing maintenance-related costs and disruptions to their operations. In addition to products developed by OEMs, some of the third-party developers of commercial data mining products include SAS Analytics, Rockwell Collins, and SmartSignal.

Several challenges exist in transferring these data mining applications to the wind industry but a number of OEMs and third-party suppliers are in the process of developing or, in some cases, field-testing wind-specific SDM software.

Contemporary Applications of SDM in Wind

Centralized remote monitoring centers are becoming a common feature of many well-established OEMs as well as some of the larger owner/operators. In most cases, these remote monitoring centers make use of conventional CMS data gathered from instrumented turbines. Some of these OEMs and operators are also adding SDM to their remote monitoring operations as a supplement to conventional CMS data in order to increase automation in data-heavy processes such as alarm management and fault prediction. GE, Vestas, and Iberdrola have all published papers and presented high-level results at conferences on the effectiveness of using SDM both as a stand-alone tool and a complementary tool for performance improvement and CM. All have remote monitoring centers equipped with the analytical software for mining both conventional CMS data as well as continually monitoring individual turbine power output signals.

Because wind parks are geographically dispersed and often in remote locations, cost considerations make it necessary to combine on-site diagnostic specialists with a centralized remote monitoring center – it is not cost-effective for each individual power plant to have its own CM capabilities. However, centralized monitoring separates the on-site specialists from expertise at the remote monitoring center. Clear procedures must therefore be implemented for accurate and consistent feedback between these two stakeholders in order to ensure appropriate machine inspections or service actions are performed.

One of the latest North American remote monitoring centers is Iberdrola's U.S. National Control Center in Portland, Oregon. This control center monitors nearly 4 GW of energy from more than 40 power plants. Each wind turbine has a control box containing a programmable logic controller (PLC), power converter, control boards, and an I/O device at the top. Sensors collect and transfer data to the PLC for factors such as wind speed, wind direction, and shaft rotation speed. Each local area network (LAN) is connected to a remote control station that manages and collects data and adjusts the turbine settings. It also provides intelligent alarm, troubleshooting, and reporting capabilities. The central control station is equipped with a third-party SCADA system that acts as a data historian and data management system for the wind farms. It connects the individual turbines, substations, and meteorological stations to the central control room. That enables the operators to supervise the behavior of all the wind farms both individually and as an integrated system.

Since Iberdrola has wind farm operators using multiple types of turbines each with distinct OEM SCADA systems and protocols, a third-party SCADA system was essential to configure these various data streams and route the acquired data back to the National Control Center. The facility has also recently been connected to CORE, the Renewable Energies Operation Centre in Spain.

Of the many OEMs surveyed in this study only Vestas, Siemens, and GE are known to currently be employing in-house SDM tools. GE specifically has published initial field-testing results for their SCADA Data Anomaly Detection Service (SDA) implemented on a Duke Energy site in February 2010. Currently GE's SDA product is included when a customer purchases GE's Bently CMS equipment and services – for the term of the warranty or services. Both CMS and SDA are included in a GE Full Service Agreement which in practice is equivalent to an extended warranty [28].

Many third-party suppliers are also actively developing SDM systems for wind turbines. Some examples of these products are discussed below.

1. Cosworth's Output Maximization System (OMS): This system combines comprehensive capture and logging of control and environmental data with Cosworth's proprietary torsional vibration sensing, neural network and predictive analysis capabilities. The result is an analysis that is intended to provide CM support and power performance improvement based on intelligent technology that anticipates problems before they occur. According to Cosworth, the OMS solution will be based on their existing Pi Diablo software which has been used for a number of years as a control and CM system for wind tunnels. This will be incorporated into new data acquisition hardware developed specifically for wind turbines. Modifications to the Diablo software platform will allow for the incorporation of signature finding and neural network technology. As with many other software developers, Cosworth's main challenge is access to turbines as well as real-time SCADA data for development and testing. As of the writing of this paper, Cosworth had an agreement in principle from a UK operator to install the system on 25 turbines as a development project. However, this project is on hold pending an agreement on real-time access to the SCADA data from the turbine OEM.
2. Rockwell Collins' Pattern-based Predictive Technology: Rockwell Collins is relatively new to wind but is leveraging its experience in other industries to develop algorithms intended to realize improved accuracy in forecasting wind conditions and impending faults. This is not a stand-alone system but rather a set of mathematical models that can utilize most third-party SCADA systems to maximize capacity factor and improve fault detection and prediction. At this stage, we are not aware of any field-testing of the Rockwell Collins pattern-based predictive technology on an operational wind site.
3. SmartSignal: Another example SDM technology being developed for the wind industry is the predictive analytic software built by SmartSignal. The diagnostic software works with SCADA data from existing sensors on a wind turbine. It compares these data to software models customized for individual pieces of equipment to provide early warning of emerging problems. SmartSignal has seen perhaps the most extensive use of any third-party SDM software applied to wind turbines and has been applied by BP Wind Energy, Iberdrola Renewables, Duke Energy, enXco, and Invenergy among many others. Discussions with some of these owners and operators have shown

that the software is a useful tool for detecting a wide variety of failures, specifically blade pitch and yaw motor failures, gearbox failures, as well as voltage and current failures. In addition the software has the potential to detect performance problems in individual turbines through comparison across a wind plant. When paired to the PI SCADA and data historian system some operators have claimed annual fleet-wide benefits nearing $750,000 [21].

SDM as a Third-Party Service: Barriers to Commercialization

Despite a recent development push, remote monitoring using SDM of the turbine power output signal is not yet commercially widespread in the wind industry as a third-party service. The potential benefits of this technology are well-understood and subsequent chapters will explore in more detail the degree to which SDM can help improve a wind project's performance and reliability. However, significant barriers to commercialization of a service-based SDM offering still exist.

Some of the challenges currently facing the wide-spread commercialization of this technology as a third-party service include:

- Third-party access to OEM SCADA data and protocols: Generally OEMs are reluctant to divulge real-time project data to project owners, especially data relating to faults and failures. OEM warranty and service agreements often specify that monthly reports containing averaged, typically 10-minute, data will be provided to project owners. This type of low-frequency data severely limits the capabilities of a technology such as SDM which thrives on large volumes of representative data especially for the purposes of pattern recognition and failure prediction. To be successful, a third-party system requires the capacity to communicate with the OEM system and any CMS instrumentation (if available) in order to make full use of the potential value of the post-warranty O&M market.
- Developing machine-specific algorithms: Unique software models and algorithms will need to be developed and tailor-made for each OEM data historian and each turbine model. Although some base algorithms may be transferable from one machine to another, the coefficients and parameters used in the equations would need to be calibrated for each specific turbine model. The development and specification of these coefficients and parameters are essential to the process. A third-party developer would need to consider the cost, coordination, and data required to develop such machine-specific models and algorithms.
- Condition of SCADA hardware: Older wind projects may not have adequate SCADA communication speeds and the requisite system reliability to effectively contribute to SDM. These projects may require SCADA system upgrades allowing for faster and more reliable data transfer which may include improvements in cable networks, servers and other hardware. Some

older projects are investing in upgrades to wireless point-to-point and point-to-multipoint communication connections which are available with speeds of up to 300 Mbps and the necessary bandwidth for data transfer to a remote monitoring center.

- Product development: Although this technology has been examined and tested by academics, turning academic research into a commercial product requires the involvement of a commercial software developer. Most importantly, however, this should not be just a product but rather a service with the product being supported by experienced personnel with the appropriate know-how. One major challenge to the commercialization of this technology is the time required to developing in-house SDM knowledge and expertise as few of these experts are available in the industry.
- Cost-justification: This is critical to the commercial success of any new technology. For instance, the benefit of SDM in offshore wind lies in its ability to detect faults and thereby confirm/deny fault alarms. Pitch systems, electrical systems and controls are notorious for causing false alarms and many cannot be remotely reset. This is usually not a big problem onshore but can be very costly offshore if, in order to get a turbine running again, a technician has to be sent to the turbine for a diagnosis and reset. Identifying the business case for onshore SDM applications is an important first step in its commercialization as a third-party service in the U.S.

Section 4: SCADA Data Mining – Costs and Capabilities

SDM for Improving Power Performance

Historically, the wind industry has placed a great deal of emphasis on turbine availability; however, the power performance of the turbine when it is up and running is also critical to overall project profitability. Underperformance has a direct impact on a project's revenue stream (kW-hours produced) but it can also be indicative of component degradation or failure. This section will discuss how SDM can be used to improve a wind plant's profitability through performance monitoring, power curve analysis, and improved power forecasting.

Power Performance Optimization

Most operators manage their wind turbines 'in abstract' using ideal power curves. However, the reality is that within a project power curves vary from one individual machine to another – even across machines of the same model. Data mining can help optimize the operation of a wind turbine by developing a power curve for individual machines based on constant monitoring of available SCADA data. This power curve can then be adjusted over the life of the project as the machine ages and its power profile changes. This approach has already been applied successfully to combustion turbines with several commercially available data-mining products [20].

There are a number of potential causes for wind turbine underperformance. These include environmental factors such as icing or turbulence, which can degrade the aerodynamic performance of the turbine, as well as causes intrinsic to the turbine such as control system faults, sensor faults, generator faults, or even structural issues in the turbine main-body. Power performance optimization or "performance monitoring" refers to the use of a wind plant's SCADA data stream to identify these causes of underperformance and optimize the output of individual turbines within a project. It is important to decouple a turbine's power performance from availability as a turbine can be severely underperforming and yet still register as 100% available (see Figure 4-1).

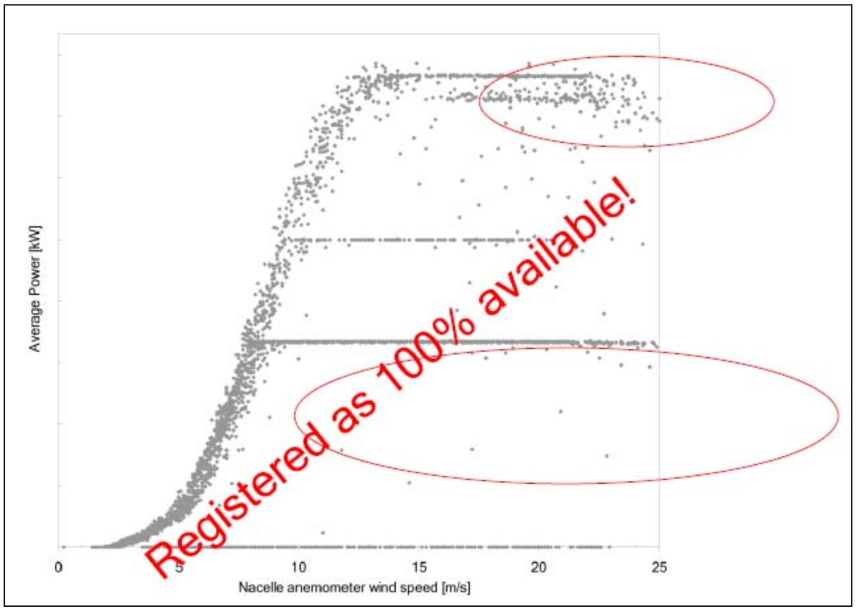


Figure 4-1
Example Turbine Underperformance [23]

Performance monitoring is a purely statistical exercise, and uses the SCADA data that are already routinely recorded to investigate the relationships that describe how one parameter – such as output power – varies in response to another – such as input wind speed. The observed relationships are tracked over time as the wind varies and each turbine responds to this variation in a manner characteristic of its age and condition.

Figure 4-2 below shows a typical case of turbine underperformance. In extreme cases, where several turbines on a single project experienced such levels of underperformance, losses were estimated to be on the order of US$150,000/month [22]. Whereas a manual exercise in SCADA data analysis could very well yield a similar estimate, such a process requires time, skill, and expertise and can be quite expensive. In order to perform routine performance monitoring using real-time data it is essential to automate the process using an SDM software-based approach. Another valuable aspect of SDM is its ability to visualize results in a variety of graphical forms allowing the operator to quickly and accurately evaluate the relationship between parameters and support rapid assessments of a project's overall performance.

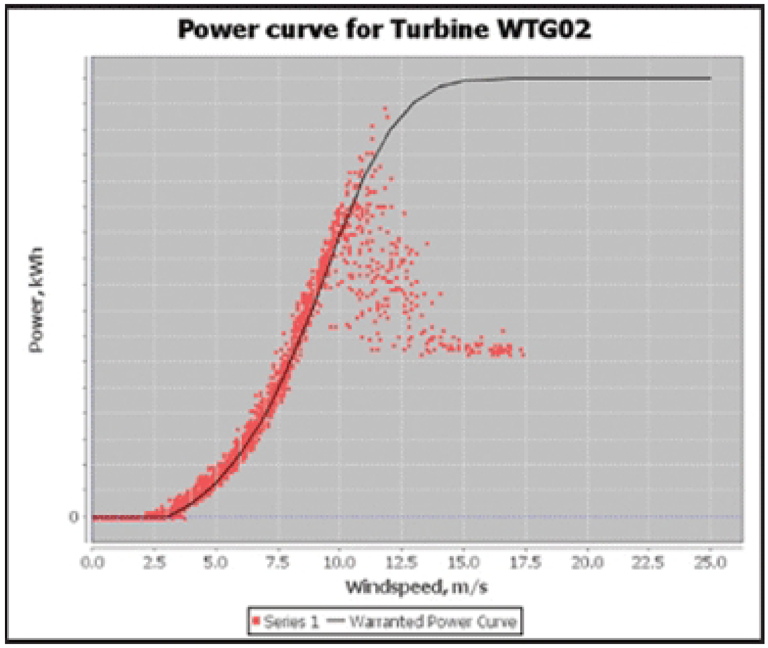


Figure 4-2
Power Curve Analysis Showing Turbine Underperformance

Actual power performance data may deviate from the nominal power curve for a variety of reasons. Inherent variation in the system is prevalent even under normal circumstances; therefore, being able to differentiate normal from abnormal power performance and turbine behavior across thousands or even millions of data-points becomes critical to identifying underperformance. Checking turbine performance data against the nominal power curve requires, first and foremost, a fitting of each discrete data point to the nominal power curve. This initial step is essential to data-driven diagnostics and several methods of fitting the data have been developed with varying degrees of success [25].

Performance monitoring can be done independently of, or as a complement to, condition monitoring. As performance monitoring makes use of data that are already acquired, no additional hardware needs to be installed and therefore the investment is seen as lower risk than CMS which are much more hardware-dependent. In addition, because it does not require any physical modifications to the turbine itself, SDM can be compatible with warranty terms and should not incur any downtime at installation.

Algorithms capable of using a turbine's historical performance trends against error and alarm codes can identify, for instance, where curtailment events coincide with specific alarms. When used in combination with CM, this can strengthen the argument for preventive maintenance. In the absence of instrumented CMS, such evidence may offer initial clues that something may be wrong. Academic researchers have estimated that using SDM for the purposes of power performance improvement could yield revenue improvements of anywhere from 1% to 5%. The University of Iowa's department of mechanical and industrial engineering claims to have demonstrated nearly a 10% increase in power output for one particularly underperforming turbine by using a high-frequency SDM approach. However, it is not likely that these types of performance optimization results are achievable for a majority of commercial wind projects. It may be possible to increase power output by 5%-10% for specific turbines that have significant undiagnosed operating problems (e.g., bad pitch settings, operating off yaw, and so on.), but for the majority of operational turbines it is much more reasonable to expect an average of 1% to 2% improvement on aggregate for an entire wind farm. This assumes that nothing significant is done to physically alter the wind turbines.

Improving Power Forecasting

Wind power forecasts are used as input for a variety of purposes. Short-term forecasts (1 to 12 hours in advance) are used for day-to-day purposes and on-site management decisions whereas long-term models (up to 84 hours in advance) inform higher-level strategic decision-making and operations management. Accurate power forecasting is essential to a wind project whether that asset is committed to predetermined production levels under a power purchase agreement (PPA) or selling power on the open market.

Physics-based and statistical modeling approaches have been widely used to forecast wind speed and expected wind plant power production. The two methods have advantages and disadvantages but both are challenged by the stochastic nature of wind - this is true for both short-term and long-term predictions. Even assuming that an accurate wind speed prediction exists, wind farm power forecasting cannot be guaranteed, as the status of each wind turbine determines the ultimate power output. Data mining and performance monitoring can help increase the accuracy of production forecasts by better relating how each turbine will translate projected inflow conditions into kilowatt-hours.

Data mining approaches to forecasting wind plant performance are based on adaptive algorithms that can be made more accurate as weather-related and operational data are made increasingly available. For instance, trending the seasonal performance of turbines is dependent on having at least one year of data showing monthly variations in performance upon which predictive algorithms can draw. The effectiveness of using SDM for power forecasting is therefore dependent on both the quantity and quality of available SCADA data [24].

SDM for Condition Monitoring

Conventional CMS play a pivotal role in establishing a preventive maintenance approach. Such an approach can be much more effective at maintaining desired turbine availability and controlling turbine O&M costs than a corrective or reactive maintenance plan. However, CMS requires the deployment of a variety of sensors as well as computationally-intensive and labor-intensive analysis techniques – a typical CMS costs approximately $10,000 per turbine [26]. This section discusses the advantages of instead using SDM for the purposes of CM.

SDM has a proven history of aiding in both the diagnosis and prognosis of turbine faults and component failures. Efficient fault prediction and fault detection algorithms can be developed to provide early warnings of mechanical and electrical defects and prevent major component failures as well as knock-on effects on other components. This allows a project operator to better plan for unscheduled maintenance events, such as optimizing crane logistics and minimizing downtime.

Finally, applying fault detection and fault prediction algorithms in data mining software effectively removes much of the human element from the data analysis process. Although experts can and should be used to complement the analysis when needed, for instance through the support of a 24-hour remote monitoring center, there is usually so much data that the level of automation provided by SDM allows for more effective and efficient fault detection and fault prediction capabilities.

Impacts on Plant Reliability

Fault detection algorithms evaluate measured process data in order to isolate incipient faults at a very early stage before they become optically, acoustically or otherwise detectable. A data mining approach can therefore detect many faults while the defective component is still operational. Necessary repair actions can then be planned in time and need not be taken at the time of failure. This is especially critical for remote and offshore wind plants where difficult conditions can restrict access and thus delay repair actions.

One way to achieve this is to build fault detection and fault prediction algorithms on the basis of prescribed performance parameters, incorporating into these algorithms all the likely causes of detection and failure, and then devising an intelligent alarm or indicator to alert the operator of an impending fault.

Three-phase total power monitoring has been applied to wind turbines as a CM and fault detection tool but has not yet achieved widespread commercial use. This technique's advantages include [14] [15]:

- Unlike conventional CMS, which requires complex and lengthy collaboration between operators and manufacturers in the field, this technique, is easily validated on a test turbine with a simple fault setup.
- Conventional CMS mainly employs Fourier transform-based techniques to process wind turbine signals. While efficient, this algorithm has limitations in dealing with non-stationary signals, leading to frequent (and expensive) false alarms. SDM tools monitoring the generator total power signal have been successfully tested using continuous-wavelet-transform (CWT) based methods which reduce calculation times and are more efficient at detecting faults in variable-speed turbines.
- The technique can be applied to any wind turbine for tracking any fault whether mechanical or electrical as long as that fault has a detectable frequency component in the three-phase total power output signal.

One example of an SDM tool being used for the purposes of condition monitoring and developing preventive maintenance tasks is SIMAP [27]. This software application was developed for the Spanish wind energy company *Molinos del Ebro*, S.A. SIMAP makes use of a variety of wind turbine sensor and power readings typically used for turbine control purposes but whose data streams can also be used to feed the development of a preventive maintenance plan. Both health CM and fault detection are based on normal behavior modeling where real operational data are used to characterize the normal dynamics of representative variables of a turbine's operation. A subsequent module is used to detect anomalies in the turbine's operation by comparing measured values with expected values from the normal behavior model in order to:

1. Diagnose root causes of the detected symptoms
2. Assess current health/condition of components
3. Forecast remaining life of components
4. Develop a dynamic preventive maintenance plan

The advantages of applying a preventive maintenance plan include:

- Maintenance intervals are frequently better adapted to the real needs of the wind turbine than when using a reactive or planned maintenance strategy with fixed maintenance intervals, because the real-time condition of the turbine is taken into account.
- Turbine life cycle is optimized by applying a maintenance strategy that effectively delays or reduces component degradation – this has the potential to extend the life of wind power project.
- The actual effectiveness of applied maintenance actions is increased as effective root-cause diagnosis can identify the most appropriate mitigations.

One of the most successful and well-documented applications of SIMAP is in the condition monitoring of gearboxes. Because the power produced by the wind turbine generator is proportional to the wind speed (up to rated power) and consequently to the rotor speed (for variable speed turbines), the health of the gearbox depends mainly on a selection of working and environmental conditions. For instance gearbox temperature can be estimated by tracking the following variables: generated power, nacelle temperature and the status of the cooling system, which can be measured by digital signals from the cooler fans. Figure 4-3 shows the typical relationships among all these variables as monitored over a 2 week period.

Once the normal behavior of the gearbox can be established in relation to these measurable variables, it then becomes possible to perform remote monitoring of the gearbox and detect selected deviations and faults. The gearbox is one of the most critical components in the maintenance of a wind turbine and is responsible for around 15–20% of its maintenance costs and unscheduled downtime. However, similar fault detection and CM techniques have been developed for almost all major components in a wind turbine. Algorithms for the diagnosis and prognosis of the following mechanical and electrical faults have been documented in the literature:

- Generator stator winding fault
- Full short circuit fault
- Rotor imbalance fault
- Drive train mechanical fault

Preventive maintenance plans developed using these techniques can help reduce the likelihood of these unscheduled maintenance events and minimize the cost of repair and replacement should a failure occur [27].

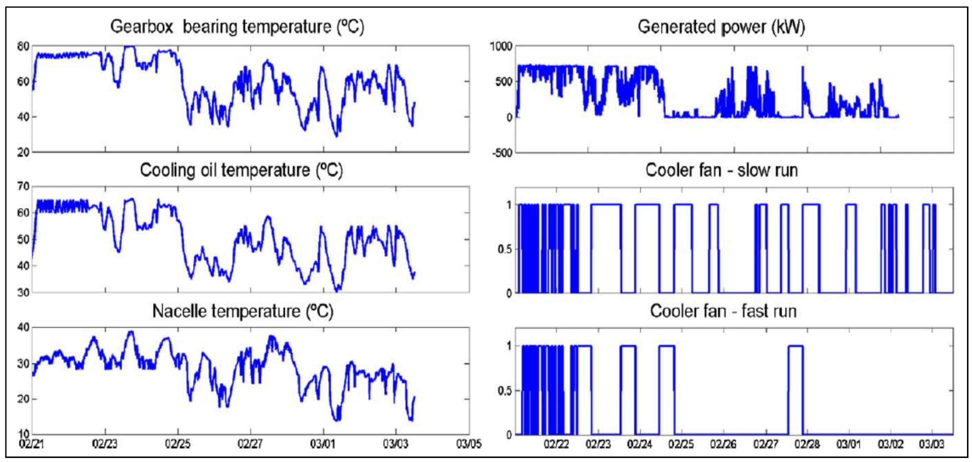


Figure 4-3
Temporal Evolution of Gearbox Main Variables [27]

Impact on O&M Costs and Turbine Availability

The application of SDM for the purposes of CM and fault detection has been shown to have a significant benefit to wind farm operations.

The main objectives of remote CM are avoiding or delaying the replacement of major components, thereby reducing unscheduled maintenance costs, optimizing utilization of resources (cranes, labor, etc.), limiting collateral damage, minimizing downtime, and reducing inventory costs. The potential savings resulting from the remote CM of gearboxes can be used as an example. With no remote monitoring of the gearbox damage occurs without warning, often resulting in catastrophic failure requiring unplanned replacement of the component. This requires shutting down the turbine and hiring a crawler-type crane to remove the rotor and replace the gearbox, costing up to $250,000 (including crane costs), and four to eight weeks of downtime. With CM in place indicators for gearbox damage can help diagnose problems at an earlier stage. At the very least, if component replacement is still necessary, maintenance can be scheduled around the wind, with cost savings of up to 50% per event and a downtime of one or two weeks. At best, the diagnosis can alert the operator to a potential corrective action that can prevent or delay the damage altogether.

Another potential for cost savings involves end of warranty (EOW) inspections. It is common industry practice to perform full visual inspections of all gearboxes at EOW; however, not all gearbox subcomponents can be adequately inspected in the limited time reserved for EOW inspections. With CM the inspection focus on the gearboxes that show indicators for wear/damage and these in turn can be inspected in a more thorough manner.

Finally, for turbines that already have conventional CMS, SDM tools can also help by confirming or denying faults and alarms. This is valuable for turbines in remote locations (and especially for projects in the offshore environment) where visual confirmation and re-start is not possible or difficult to perform. In addition, conventional CMS is limited in what it can measure. The addition of SDM can help identify and monitor an entirely different set of faults, namely electrical faults, which are among the most frequent failure types in wind turbines (see Figure 2-6).

A limited number of data points exist providing the actual cost savings recorded by wind projects as a result of implementing SDM tools for the purposes of condition monitoring. GE's SDA service provides in-house data-mining software support and utilizes algorithms developed by GE Aviation Systems and GE Wind for the purposes of performance and CM of wind turbines. GE is currently monitoring upwards of 8,000 turbines using this software, which has helped GE avoid over $8MM in GE warranty costs in the 12-month period between mid-2009 and mid-2010. At the project level, a GE case study on the implementation of their CMS and SDA services at the Campbell Hill Wind Farm revealed O&M cost savings of over 20% (see Figure 4-4) as well as increased project revenue [28].

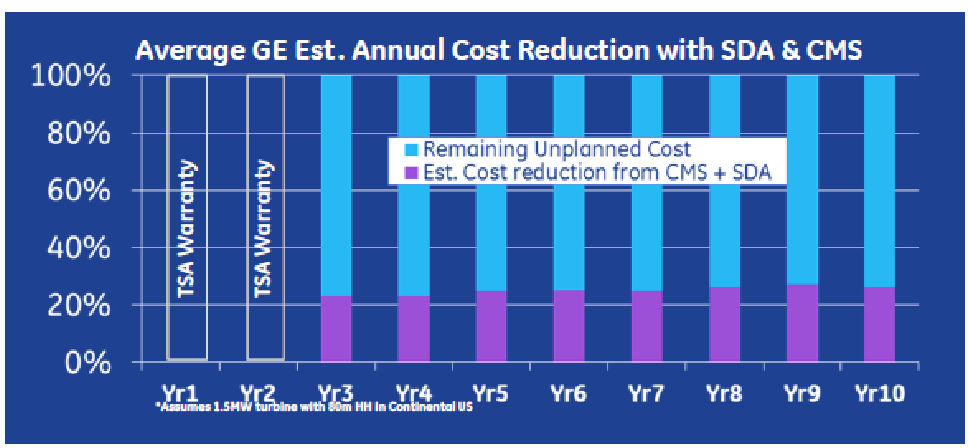


Figure 4-4
Expected Annual O&M Cost Reduction – GE Campbell Hill Case Study [28]

The decrease in costs was driven primarily through avoided damage to components, a reduction in down tower repairs and optimization of crane and labor schedules, maintenance resources, and on-site parts inventory. The increase in revenue was achieved primarily through the resulting increase in availability as well as performance optimization. It is clear from GE's experience that net benefits in availability are proportional to the level of O&M cost reduction achieved over a specific time period. The ability to better manage unplanned failures has a very similar impact on turbine downtime as it does on O&M costs.

Table 4-1 provides a summary of the estimated benefits of using SDM for the purposes of CM, fault diagnosis and preventive maintenance. These potential impacts are based on a combination of 1) the expected benefits suggested by academic research and 2) what can be gathered from recent OEM experience testing in-house SDM tools. Two different turbine categories are considered here:

1. Sub-MW turbine that has been in operation for at least 5 years – this turbine does not have a conventional CMS installed
2. Modern, multi-MW turbine – this turbine comes with pre-installed CMS

In both cases, it is assumed that the project is located onshore in the U.S. and that time-based availability prior to implementing SDM is 95%.

Table 4-1
Summary of Expected Benefits from SDM for Condition Monitoring

	Years 1-5		Years 6-20	
	O&M Cost Reduction	Availability	O&M Cost Reduction	Availability
Base Case	-	95%	-	95%
Sub-MW Turbines	-	95%	20%	96%
Multi-MW Turbines	5%	95.3%	10%	95.5%

A 5-year old sub-MW machine typically has no CMS installed and as such has the greatest potential for improvement. It is expected that, if implemented at year 6 of operation, SDM could reduce O&M costs by 20% per year. A proportional decrease in turbine downtime can be expected. Assuming 95% time-based availability (5% downtime) in years 1 through 5 this would equate to a 20% reduction of downtime starting year 6 yielding a time-based availability of 96%. Retrofitting sub-MW turbines with a $10,000 CMS is typically not economically feasible. First, these turbines have been operational for years and thus have a shorter lifespan from which to draw a benefit from CMS. Second, because CMS is installed on a per-turbine basis they are more costly on a per-MW basis than larger turbines.

Modern, multi-MW machines typically already benefit from CMS and therefore have potentially less to gain from SDM. However, as mentioned, SDM is unique in its ability to diagnose and forecast electrical faults in addition to acting as an independent check for the CMS. As such, it is estimated that implementing SMD could reduce O&M costs by 5% annually in years 1 through 5 and 10% annually after year 6. This assumption is based on the fact that the value of condition monitoring increases as the turbine ages and component wear leads to higher failure rates. Assuming a base case of 95% availability, 5% and 10% reductions in downtime would yield a time-based availability of 95.3% and 95.5% respectively.

SDM Costs

There are several costs associated with the development of a SDM system for wind power plants, including:

- Initial Capital Investment (CAPEX):
  - Development of machine-specific algorithms
  - Model validation
  - Hardware (Server, data connection, and so on)

The costs of providing a third-party remote monitoring service using SDM tools were also estimated and include:

- Operational Cost of Remote Monitoring Center (OPEX):
  - Labor (3 shifts of 2 technicians/engineers, plus a supervisor)
  - Overhead (building, administrative, travel)

The total cost for the development of a turbine-specific SDM software model is estimated to be approximately $350,000, with a typical range from $330,000 to $455,000 including the costs described below and summarized in Table 4-2. The cost of running and operating a 24-hour remote monitoring center is estimated to be approximately $100,000 per month, with a typical range from $95,000 to $130,000. These cost estimates are for a typical onshore project in the U.S. but costs may vary from site to site depending on the quality of available SCADA data as well as variety of other project-specific factors. For all of these cost estimates we conservatively estimate a triangular distribution of -5% / +30%.

Table 4-2
Summary of SDM Capital Costs and Operational Costs

Cost	Typical	Low	High	Comment
Model Development	$150,000	$142,500	$195,000	Assumes 2 software engineers full-time for 3 months
Model Validation	$150,000	$142,500	$195,000	6 months of monitoring
Hardware	$50,000	$47,500	$65,000	Cost for purchase of hardware included. 2TB server
Total CAPEX	$350,000	$332,500	$455,000	
OPEX: Labor	$40,000	$38,000	$52,000	Per month
OPEX: Overhead	$60,000	$57,000	$78,000	Per month
Total OPEX	$100,000	$95,000	$130,000	Per Month

Model Development Costs

Developing an SDM software model involves writing of a number of algorithms for the detection of faults and analysis of power curves. Although the underlying architecture of the algorithm is transferable from turbine to turbine, each turbine model requires its own sets of parameters and machine-specific inputs. Academic researchers have undertaken the development of these software packages and turbine-specific algorithms in order to execute the research described in the literature review. Their experience has shown that on average it takes two software engineers three months full-time to develop the algorithms for a workable SDM software model.

When estimating the cost of developing a commercial application of this technology, we assume two full-time software engineers hired for three months at an hourly rate of $150. The cost of hiring a third-party supplier to develop a machine-specific SDM model is therefore assumed to be $150,000 (-5%/+30%).

Model Validation Costs

Once the model has been finalized it needs to be validated against operational project data. Generally, the academic community is given very little access to operational projects and as such many of the algorithms discussed in the literature review were not validated. Conservative estimates suggest that a thorough validation of the model should allow at least 6 months. In a 6-month period it is likely that any one wind power project will experience enough faults, component failures, and seasonal variations in performance to test and validate all functionalities of an SDM model.

The machine-specific model is expected to be validated in the context of an operating project and as such is expected to yield some benefit for that project. We assume the third-party software developer will bear no more than 50% of validation costs. Assuming one dedicated engineer for 6 months at an hourly rate of $150, the cost of hiring a third-party supplier to validate a machine-specific SDM model is assumed to be $150,000 (-5%/+30%).

Hardware

This software is expected to require significant computational processing capacity. We assume that a 2 Terabyte server will be required for both the development and operations of the SDM software. The one-time purchase and installation cost of a 2 TB server is assumed to be $50,000 (-5%/+30%).

Operational Costs of a Remote Monitoring Center

The cost of running a 24-hour remote monitoring center to support and service wind projects with installed SDM software is assumed to total $100,000 monthly or $1.2 million annually (-5%/+30%). This estimate is based on three rotating shifts of 2 engineers per shift and a supervisor. In addition, overhead costs such as building fees, travel expenses, administrative costs and general upkeep and maintenance of all computers, the main server and a high-bandwidth data connection are assumed in the total.

Section 5: Economic Assessment of SDM Applications

Introduction

Despite promising academic research and successful field testing by OEMs, SDM for the purposes of power performance improvement and CM is not yet commercially widespread as a third-party service.

The commercial case for remote monitoring services by a third party is straightforward. Major operators such as Iberdrola and OEMs like Vestas and GE have already demonstrated the benefits of centralized 24/7 remote monitoring of wind turbines by investing in their own centralized control centers [28][29]. However, these groups benefit from economies of scale of thousands of wind turbines as well as access to the human and financial capital necessary to develop and operate these centers. Smaller operators and OEMs new to the wind market have found that in order to benefit from the same level of continuous monitoring, third party service-providers are their best option.

Generally, the further removed a project is from the OEMs, the more use that project has for third-party services. This is evidenced by the growing trend of turbine CM being outsourced to specialists. China's fourth largest wind turbine manufacturer, Guohua, recently hired SKF to install their WindCon turbine monitoring system across nearly 300 turbines. Those turbines will be monitored remotely at SKF's Intelligent Centre Wind (ICW) facility in Hamburg, Germany. Schenk Balancing and Diagnostics Systems (Schenk) is another third-party provider of remote monitoring services. Schenk offers expertise to supplement installed CMS instrumentation for 24/7 monitoring of turbines. They provide notifications in case of irregularities, explanation of measurements, trend curves and recommended actions. This third-party service model has been effectively implemented for conventional condition monitoring systems. In this chapter we examine their applicability to SDM technology.

SCADA Data Mining Economic Analysis

SDM software models can typically be incorporated into existing enterprise SCADA system architecture (such as OSIsoft's PI software or Emerson's Ovation platform) as these typically allow add-ins and third-party algorithm development. Because these data historians are already widely used in the wind industry and SDM does not require any additional hardware, SDM-based condition-monitoring and performance-monitoring can be offered completely remotely by a third party. Since data-mining algorithms are adaptive, as the turbine population being monitored grows, so will the confidence and predictive power of the application.

In this study, three probabilistic cost benefit analyses were run to show the potential change in cost of energy (CoE) and Net Present Value (NPV) for (1) a 750 kW turbine retrofitted with SDM software and with 15 years of remaining life, (2) a 2.5 MW turbine with conventional CMS and SDM and with 20 years of remaining life, and (3) a 2.5 MW turbine with conventional CMS and SDM and with the potential for extended life (20+ years) as a benefit of SDM. CoE is estimated using the EPRI-TAG method. The Palisade software program, @Risk, was employed to execute a stochastic simulation of the cost model to obtain the uncertainty in the results.

The results are highly dependent upon the baseline turbine selected. For example, the benefit to a turbine with chronic gearbox failures may be more significant than to one with no gearbox failures; though the use of a SDM would not solve the problem it may, for example, provide additional warning of the impending failure and reduce repair/replacement costs. For the purposes of this study, it was assumed that the turbine design is mature and hence robust. The 750 kW base case turbine was created such that its characteristics are generally representative of a typical 5-8 year old turbine. The 2.5 MW base case turbine was created such that its characteristics are generally representative of a 1-2 year old onshore wind turbine. These characteristics include, amongst others, capital costs, O&M costs, total availability, downtime due to maintenance, capacity factor, etc.

Because wind turbines are highly engineered complex machines, many of the benefits that will be assumed in this study will likely require real-world compromises that impact their efficacy. However, for the purposes of this study the optimistic assumption was made that the benefits can be achieved without negatively impacting other aspects of the turbine design and cost.

There are a number of benefits of using SDM for the purposes of CM and power performance improvement, four of which were quantified in terms of economics:

1. Increased power performance due to optimization of the power curve.
2. Increased lifetime energy capture due to longer life, as a result of CM and a preventive maintenance approach.
3. Reduced O&M costs due to optimized maintenance planning and reduced failure rates.
4. Increased turbine availability due to reduced downtime for maintenance, assuming fewer component failures.

These economic benefits are matched with the three analyses in Table 5-1. The table shows which analysis will include which benefit; note some benefits are mutually exclusive and cannot be included in the same analysis. Insurance premiums are also expected to decrease, but this is not quantified in the analysis because the uncertainty on the decrease is greater than the expected decrease itself.

Table 5-1
SDM Economic Analysis Scenarios

Scenario/ Benefit	Case 1	Case 2	Case 3
	750KW Turbine, Retrofitted SDM	2.5MW Turbine, CMS & SDM	2.5MW Turbine, CMS & SDM (Extended Life)
Increased power due power curve analysis	X	X	X
Increased lifetime energy capture due to longer life			X
Reduced O&M costs	X	X	X
Increased availability due to reduced O&M related downtime	X	X	X

The cost model inputs are described below:

1. Turbine Capital Costs

   The nominal capital cost of the installed turbine was assumed to be $1,800/kW, representing the costs of development, design, engineering, construction, substation/interconnection, financing/legal, as well as the capital costs of the equipment. The uncertainty on this nominal installed cost is $200/kW.

2. SDM Software Capital Costs

   The cost of developing and validating the machine-specific SDM algorithms includes labor costs and hardware costs as described in the previous chapter and totals $350,000. For the probabilistic assessment a triangular distribution is used and applies a relatively conservative uncertainty of -5%/+30%.

3. Discount Rate

   For the probabilistic assessment a discount rate of 7% was assumed and a triangular distribution applied with a low value of 5.5% and a high value of 10%.

4. Turbine Operable Life

   A nominal life of 15 years and 20 years was assumed for the base case 750 kW and 2.5 MW turbines, respectively. A life extension of 2 additional years was assumed for Scenario 3 in order to test the assumption that preventive maintenance should help increase mean-time-between-failures and potentially add years of operation to the turbine.

5. O&M Costs

   A proprietary in-house O&M model was used to estimate the annual O&M costs associated with each case. As described in Table 4-1, a 5-year old sub-MW machine is assumed to experience annual reductions in O&M costs of 20%. A modern, multi-MW machine is assumed to experience annual reductions in O&M costs of 5% (years 1 to 5) and 10% (years 6 to 20). For the probabilistic assessment, a triangular distribution is used with an uncertainty of -10%/+20%.

   The resulting expected reductions in O&M costs fall in ranges of 16% to 22% for Scenario 1, and 4% to 5.5% (years 1 to 5) and 8% to 11% (after year 6) for Scenarios 2 and 3.

6. Availability

   A nominal turbine availability of 95% on time was assumed. Using a time:energy ratio of 1.2 this converts to a turbine availability of 94% on energy.

   It is assumed that turbine downtime is reduced by an amount proportional to O&M cost reductions described above. Therefore a 20% reduction of downtime is assumed for Scenario 1 which yields a time-based availability of 96%. For Scenarios 2 and 3, 5% and 10% reductions in downtime would yield a time-based availability of 95.3% and 95.5% respectively. For the probabilistic assessment, a triangular distribution is used with an uncertainty of -10%/+20%.

7. Power Performance Improvement

   It is assumed that the application of SDM for the purposes of power performance improvement could yield revenue improvements up to 5%. For the average turbine, a 1%to 2% improvement can be expected. However, the range of potential benefits differs between the two turbine types.

   In Scenario 1, a wide range of power performance improvement is assumed due to the age of the turbines and the lack of any previous performance monitoring software. A range of 0.5% to 5% improvement in revenue is assumed. Most turbines are expected to see improvements typical of the lower end of this range and as such a Weibull distribution is used for the probabilistic assessment. The Weibull distribution assumes a shape factor of 1.2 and a scale factor of 2% and the curve is truncated at 0.5% and 5%.

   In Scenarios 2 and 3, a narrower range of power performance improvement is assumed due to the presence of some sort of performance monitoring software and therefore a smaller potential for improvement. A range of 0.25% to 3% improvement in revenue is assumed. Most turbines are expected to see improvements typical of the lower end of this range and as such a Weibull distribution is used for the probabilistic assessment. The Weibull distribution assumes a shape factor of 1.2 and a scale factor of 2% and the curve is truncated at 0.25% and 3%.

8. Capacity Factor

   A capacity factor of 35% was assumed for all three scenarios and is used in combination with turbine availability to estimate total annual energy production.

9. Price of Electricity

   For the purposes of calculating base case revenue as well as changes in annual revenue with the addition of SDM, a price of $75/MWh is assumed for this study.

Scenario 1

Overview

Under Scenario 1, 100 750kW machines are retrofitted with SCADA Data Mining software. Such a large number of sub-MW machines is not typical for 5 to 8 year old wind projects in the U.S. The assumption here is that this is not a single project but rather a collaboration among several smaller projects. It is not realistic to assume that the relatively high capital costs of developing the machine-specific algorithms should be borne by a single project. Rather, this scenario assumes that several projects running the same turbine model form an owner's group and leverage their increase numbers to share the capital costs (as well as the benefits) of model development. It is expected that a third-party can develop a machine-specific SDM software tool that can be shared across various projects running the same model turbine. These projects would then be expected to pay an annual or monthly fee for remote monitoring services on a per turbine basis.

A Monte Carlo simulation was run with 10,000 iterations. The resulting distribution of all inputs and outputs of the probabilistic assessment are summarized in Table 5-2. Note that these results show the potential, not likely, outcomes.

Results

Using tools such as power curve analysis, and condition monitoring to increase turbine availability would yield an expected increase of 2.3% in net Annual Energy Production (AEP). At $75 / MWh, that equates to additional annual revenue of $4,750 /WTG at the 50% probability level (P50) and $3,250 /WTG at the 90% probability level (P90).

The condition monitoring and fault diagnosis/prognosis provided by SDM would yield a reduction in O&M costs of 20% or roughly $3,600/year per turbine averaged over the remaining 15 year project life. It is important to note that since O&M costs are expected to increase as the turbines age, the annual O&M cost savings also increase over time as they are a function of overall O&M costs.

The gross NPV of the investment in SCADA Data Mining is estimated to be $75,000 /WTG at the 50% probability level (P50) and $60,000 /WTG at the 90% probability level (P90).

Expected costs for the development and implementation of the SDM software tool are expected to be $3,750 /WTG at the 50% probability level (P50) and $3,500 /WTG at the 90% probability level (P90). The annual service fee per WTG has been estimated for three different payback periods of 5, 7.5 and 10 years (see Table 5-2).

Assuming the gross benefits described above, the annual fee per turbine that would yield a payback period of 5 years is expected to be $7,250 /WTG at the 50% probability level (P50) and $5,750 /WTG at the 90% probability level (P90). After 15 years of operation, the internal rate of return (IRR) for this investment is estimated to be 24%.

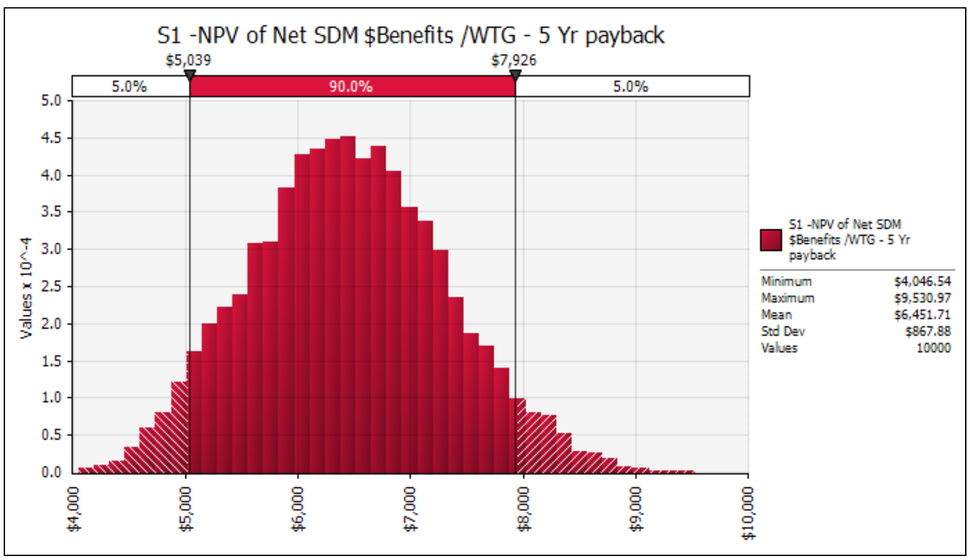


Figure 5-1
Percent Change in NPV – Scenario 1

Assuming the capital costs described above and an annual service fee yielding a 5 year payback period, the NPV of net benefits from implementing SDM for the purposes of power performance improvement (PPI) and condition monitoring are expected to be $6,500 /WTG at the 50% probability level (P50) and $5,250 /WTG at the 90% probability level (P90). The distribution of these results is shown in Figure 5-1.

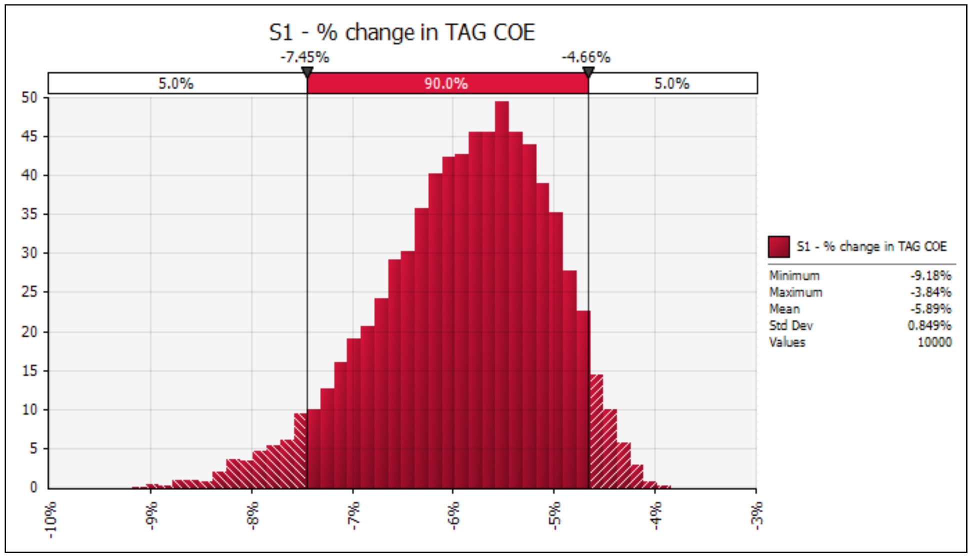


Figure 5-2
Percent Change in Cost of Energy – Scenario 1

The expected reduction in CoE is estimated to be 5.8% at the 50% probability level (P50) and 4.9% at the 90% probability level (P90). The distribution of these results is shown in Figure 5-2.

A summary of the distributions of all inputs and outputs related to the probabilistic assessment of Scenario 1 is provided in Table 5-2.

For each input and output category, the following outcomes are provided in their relevant units:

- Minimum value
- Maximum Value
- Arithmetic mean
- Value of one standard deviation
- Likely value at the 90% probability level (P90)
- Likely value at the 50% probability level (P90)

Table 5-2
Summary of Probabilistic Assessment for Scenario 1

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
OUTPUTS	S1 - Average % reduction in annual O&M Costs	16.00%	22.00%	19.30%	1.20%	17.50%	19.50%
	S1 - % change in TAG COE	-9.20%	-3.80%	-5.90%	0.80%	-4.90%	-5.80%
	S1 - Annual O&M Savings /WTG	$3,000	$4,000	$3,500	$250	$3,250	$3,750
	S1 - Annual Energy Prod Increase /WTG	$2,500	$10,250	$5,000	$1,500	$3,250	$4,750
	S1 - Average Annual $Benefit /WTG	$5,500	$14,250	$8,750	$1,500	$7,000	$8,500
	S1 - NPV lifetime additional revenue /WTG	$20,500	$97,750	$44,750	$13,000	$29,250	$43,000
	S1 - NPV lifetime O&M savings /WTG	$22,750	$39,250	$31,000	$2,750	$27,250	$31,000
	S1 - NPV of Gross SDM $Benefits /WTG	$44,250	$135,000	$75,750	$13,750	$59,250	$73,750
	S1 - NPV of Net SDM $Benefits /WTG - 5 Yr payback period	$4,000	$9,500	$6,500	$750	$5,250	$6,500
	S1 - NPV of Net SDM $Benefits /WTG - 7.5 Yr payback period	$1,500	$5,250	$3,000	$500	$2,250	$3,000
	S1 - NPV of Net SDM $Benefits /WTG - 10 Yr payback period	$(500)	$2,250	$750	$500	$100	$750
	S1 - Annual fee - 5 Yr payback period	$4,250	$12,750	$7,500	$1,500	$5,750	$7,250
	S1 - Annual fee - 7.5 Yr payback period	$4,750	$13,250	$7,750	$1,500	$6,000	$7,500

Table 5-2 (continued)
Summary of Probabilistic Assessment for Scenario 1

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
	S1 - Annual fee - 10 Yr payback period	$5,000	$13,500	$8,000	$1,500	$6,250	$8,000
INPUTS	Discount rate	5.50%	10.00%	7.50%	0.90%	6.30%	7.40%
	Capital cost of SDM development	$332,750	$454,250	$379,250	$27,000	$347,250	$374,750
	Turbine Capital Cost (/kW)	$1,500	$2,000	$1,750	$ 100	$1,750	$1,750
	% Reduction O&M costs	16.00%	22.00%	19.30%	1.20%	17.50%	19.50%
	Power Perf. Improvement	0.50%	5.00%	1.90%	0.90%	0.80%	1.70%

Scenario 2

Overview

Under Scenario 2, 100 2.5MW machines are equipped with SCADA Data Mining software in addition to previously installed conventional Condition Monitoring instrumentation and software. This project is intended to be representative of the typical large wind farm currently being developed and built in the U.S. It is assumed that, unlike Scenario 1, the capital costs of developing the machine-specific algorithms are borne by this single project with the expectation is that it has greater access to funds. Again, the project depicted in this scenario would also be expected to pay an annual or monthly fee on a per turbine basis for remote monitoring services by the third party provider, in addition to funding the development of machine-specific algorithms.

A Monte Carlo simulation was run with 10,000 iterations. The resulting distribution of all inputs and outputs of the probabilistic assessment are summarized in Table 5-3. Note that these results show the potential, not likely, outcomes.

Results

Using tools such as power curve analysis, and condition monitoring to increase turbine availability would yield an expected increase of 1.6% in net Annual Energy Production (AEP). At $75 / MWh, that equates to additional annual revenue of $9,750 /WTG at the 50% probability level (P50) and $5,250 /WTG at the 90% probability level (P90).

The condition monitoring and fault diagnosis/prognosis provided by SDM would yield a reduction in O&M costs of 8.75% or roughly $2,750/year per turbine averaged over the 20 year project life. However, since O&M costs are expected to increase as the turbines age, the annual O&M cost savings should also increase over time as they are a function of overall O&M costs.

The gross NPV of the investment in SCADA Data Mining is estimated to be $125,000 /WTG at the 50% probability level (P50) and $80,000 /WTG at the 90% probability level (P90).

Expected costs for the development and implementation of the SDM software tool are expected to be $3,750 /WTG at the 50% probability level (P50) and $3,500 /WTG at the 90% probability level (P90). The annual service fee per WTG has been estimated for three different payback periods of 5, 7.5 and 10 years (see Table 5-3).

Assuming the gross benefits described above, the annual fee per turbine that would yield a payback period of 5 years is expected to be $10,250 /WTG at the 50% probability level (P50) and $5,750 /WTG at the 90% probability level (P90). After 20 years of operation, the internal rate of return (IRR) for this investment is estimated to be 33%.

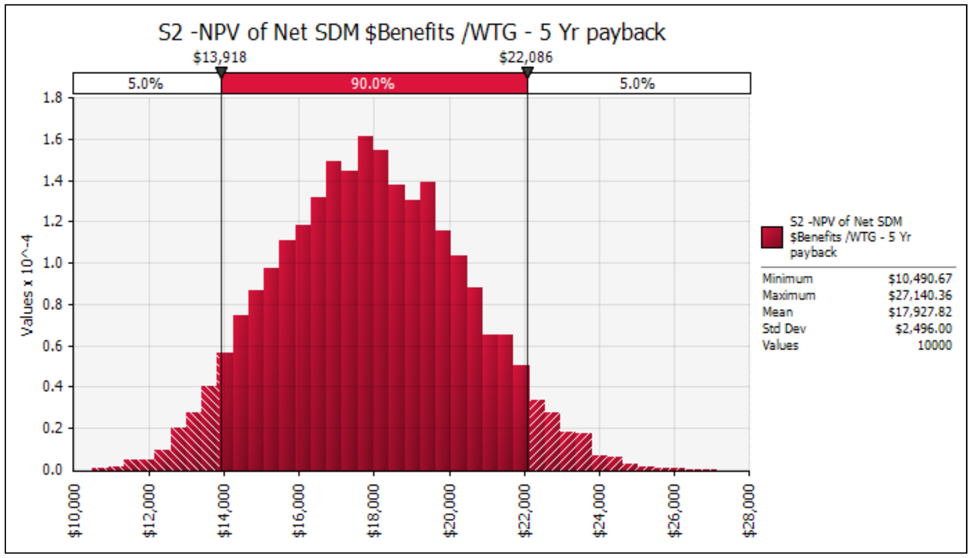


Figure 5-3
Percent Change in NPV – Scenario 2

Assuming the capital costs described above and an annual service fee yielding a 5 year payback period, the NPV of net benefits from implementing SDM for the purposes of power performance improvement (PPI) and condition monitoring are expected to be $18,000 /WTG at the 50% probability level (P50) and $14,750 /WTG at the 90% probability level (P90). The distribution of these results is shown in Figure 5-3.

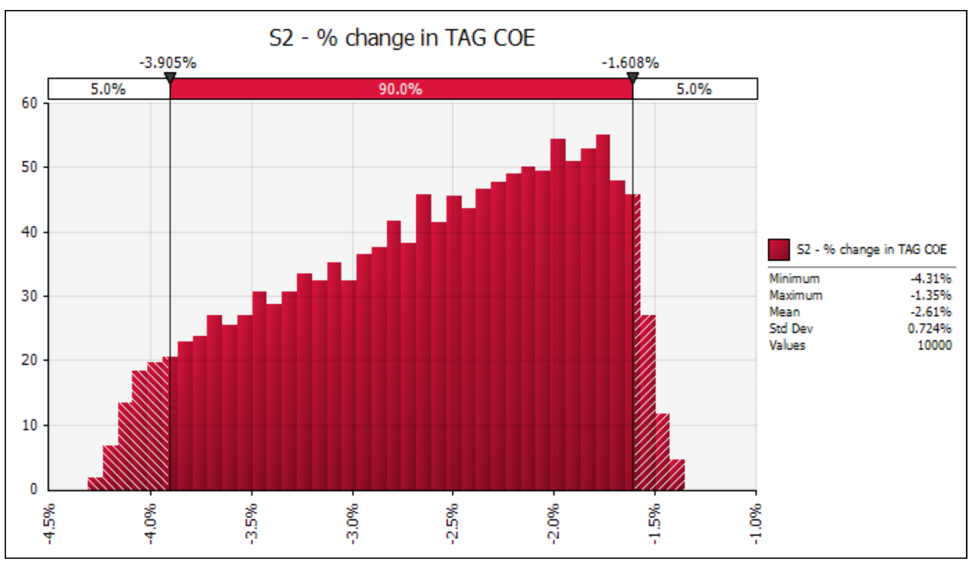


Figure 5-4
Percent Change in Cost of Energy – Scenario 2

The expected reduction in CoE is estimated to be 2.5% at the 50% probability level (P50) and 1.7% at the 90% probability level (P90). The distribution of these results is shown in Figure 5-4.

A summary of the distributions of all inputs and outputs related to the probabilistic assessment of Scenario 2 is provided in Table 5-3.

For each input and output category, the following outcomes are provided in their relevant units:

- Minimum value
- Maximum Value
- Arithmetic mean
- Value of one standard deviation
- Likely value at the 90% probability level (P90)
- Likely value at the 50% probability level (P90)

Table 5-3
Summary of Probabilistic Assessment for Scenario 2

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
OUTPUTS	S2 - Average % reduction in annual O&M Costs	7.10%	9.60%	8.50%	0.50%	7.80%	8.50%
	S2 - % change in TAG COE	-4.30%	-1.30%	-2.60%	0.70%	-1.70%	-2.50%
	S2 - Annual O&M Savings /WTG	$2,500	$3,250	$2,750	$250	$2,500	$2,750
	S2 - Annual Energy Prod Increase /WTG	$4,000	$19,500	$10,500	$4,000	$5,250	$9,750
	S2 - Annual $Benefit /WTG	$6,500	$22,500	$13,250	$4,000	$8,250	$12,750
	S2 - NPV lifetime additional revenue /WTG	$36,000	$219,500	$106,500	$42,500	$54,250	$100,250
	S2 - NPV lifetime O&M savings /WTG	$17,000	$32,750	$24,750	$2,500	$21,250	$24,750
	S2 - NPV of Gross SDM $Benefits /WTG	$55,000	$250,000	$131,250	$43,000	$80,000	$125,000
	S2 - NPV of Net SDM $Benefits /WTG - 5 Yr payback period	$10,500	$27,250	$18,000	$2,500	$14,750	$18,000
	S2 - NPV of Net SDM $Benefits /WTG - 7.5 Yr payback period	$5,750	$17,000	$10,750	$1,750	$8,250	$10,750
	S2 - NPV of Net SDM $Benefits /WTG - 10 Yr payback period	$1,750	$8,750	$4,750	$1,250	$100	$4,750
	S2 - Annual fee - 5 Yr payback period	$4,250	$20,000	$10,750	$4,000	$5,750	$10,250
	S2 - Annual fee - 7.5 Yr payback period	$4,750	$20,750	$11,500	$4,000	$6,250	$11,000

Table 5-3 (continued)
Summary of Probabilistic Assessment for Scenario 2

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
	S2 - Annual fee - 10 Yr payback period	$5,250	$21,250	$12,000	$4,000	$7,000	$11,500
INPUTS	Discount rate	5.50%	10.00%	7.50%	0.90%	6.30%	7.40%
	Capital cost of SDM Development	$335,000	$455,000	$380,000	$25,000	$345,000	$375,000
	Turbine Capital Cost (/kW)	$1,500	$2,000	$1,750	$100	$1,750	$1,750
	% reduction O&M costs (Yr 1-5)	4.00%	5.50%	4.80%	0.30%	4.40%	4.90%
	% reduction O&M costs (Yr 6-20)	8.00%	11.00%	9.70%	0.60%	8.80%	9.70%
	Power Perf. Improvement	0.30%	3.00%	1.40%	0.80%	0.40%	1.30%

Scenario 3

Overview

Scenario 3 is identical to Scenario 2 in every way except the added benefit of project life extension has been assumed. The premise for this assumption is that SCADA data mining allows the operator to correct a number of operating conditions that place unnecessary additional loads on the machine. For instance power performance monitoring may reveal that a turbine is underperforming due to off-yaw operation, blade angle asymmetry or some other controls-related issue that, if corrected, would serve to reduce loads in addition to increasing power output. Similarly, condition monitoring would drive the development of preventive and condition-based maintenance strategies which has a goal of maximizing the useful life of turbine components. As a result, this scenario assumes the additional benefit of 2 years of extended life for the turbines.

Again, in addition to funding the development of machine-specific algorithms, the project depicted in this scenario would also be expected to pay an annual or monthly fee on a per turbine basis for remote monitoring services by the third party provider.

A Monte Carlo simulation was run with 10,000 iterations. The resulting distribution of all inputs and outputs of the probabilistic assessment are summarized in Table 5-4. Note that these results show the potential, not likely, outcomes.

Results

Using tools such as power curve analysis, and condition monitoring to increase turbine availability would yield an expected increase of 2.3% in net Annual Energy Production (AEP) in years 1 through 20. At $75 / MWh, that equates to additional annual revenue of $10,000 /WTG at the 50% probability level (P50) and $5,500 /WTG at the 90% probability level (P90).

The condition monitoring and fault diagnosis/prognosis provided by SDM would yield an reduction in O&M costs of 8.75% or roughly $2,750/year per turbine averaged over the 22 year project life. However, since O&M costs are expected to increase as the turbines age, the annual O&M cost savings should also increase over time as they are a function of overall O&M costs.

The gross NPV of the investment in SCADA Data Mining is estimated to be $176,000 /WTG at the 50% probability level (P50) and $125,000 /WTG at the 90% probability level (P90).

Expected costs for the development and implementation of the SDM software tool are expected to be $3,750 /WTG at the 50% probability level (P50) and $3,500 /WTG at the 90% probability level (P90). The annual service fee per WTG has been estimated for three different payback periods of 5, 7.5 and 10 years (see Table 5-4).

Assuming the gross benefits described above, the annual fee per turbine that would yield a payback period of 5 years is expected to be $10,250 /WTG at the 50% probability level (P50) and $5,750 /WTG at the 90% probability level (P90). The 2 years of extended life does not affect this calculation since those benefits are not experienced in the first 5 years of project operations.

After 22 years of operation, the internal rate of return (IRR) for this investment is estimated to be 35%.

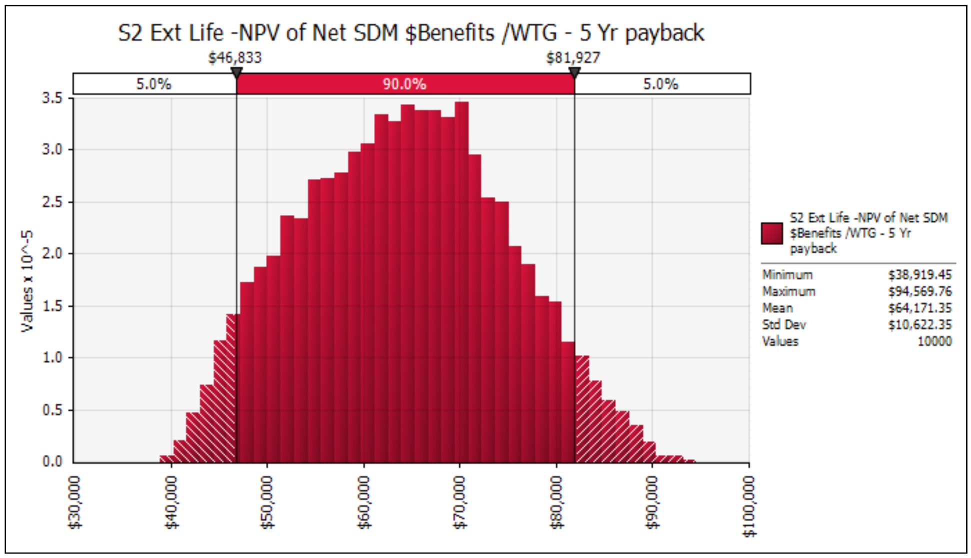


Figure 5-5
Percent Change in NPV – Scenario 3

Assuming the capital costs described above and an annual service fee yielding a 5 year payback period, the NPV of net benefits of implementing SDM for the purposes of power performance improvement (PPI) and condition monitoring are expected to be $64,000 /WTG at the 50% probability level (P50) and $50,000 /WTG at the 90% probability level (P90). The distribution of these results is shown in Figure 5-5.

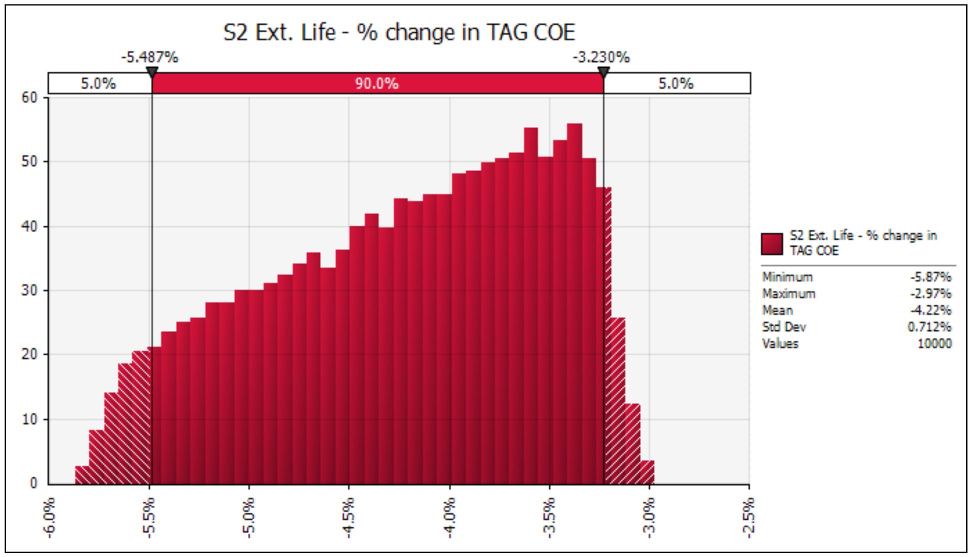


Figure 5-6
Percent Change in Cost of Energy – Scenario 3

The expected reduction in CoE is estimated to be 4.1% at the 50% probability level (P50) and 3.3% at the 90% probability level (P90). The distribution of these results is shown in Figure 5-6.

A summary of the distributions of all inputs and outputs related to the probabilistic assessment of Scenario 3 is provided in Table 5-4.

For each input and output category, the following outcomes are provided in their appropriate units:

- Minimum value
- Maximum Value
- Arithmetic mean
- Value of one standard deviation
- Likely value at the 90% probability level (P90)
- Likely value at the 50% probability level (P90)

Table 5-4
Summary of Probabilistic Assessment for Scenario 3

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
OUTPUTS	S3 - Average % reduction in annual O&M Costs	7.20%	9.70%	8.60%	0.50%	7.90%	8.60%
	S3 - % change in TAG COE	-5.90%	-3.00%	-4.20%	0.70%	-3.30%	-4.10%
	S3 - Annual O&M Savings /WTG	$2,500	$3,250	$3,000	$250	$2,750	$3,000
	S3 - Annual Energy Prod Increase /WTG	$4,000	$19,500	$10,500	$4,000	$5,500	$10,000
	S3 - Annual $Benefit /WTG	$6,500	$22,750	$13,500	$4,000	$8,250	$12,750
	S3 - NPV lifetime additional revenue /WTG	$67,500	$293,250	$155,500	$45,750	$100,000	$149,500
	S3 - NPV lifetime O&M savings /WTG	$18,000	$35,500	$26,500	$3,000	$22,500	$26,500
	S3 - NPV of Gross SDM $Benefits /WTG	$87,500	$326,250	$182,000	$47,000	$125,000	$176,000
	S3 - NPV of Net SDM $Benefits /WTG - 5 Yr payback period	$39,000	$94,500	$64,250	$10,500	$50,000	$64,000
	S3 - NPV of Net SDM $Benefits /WTG - 7.5 Yr payback period	$33,500	$84,500	$56,500	$10,000	$43,000	$56,750
	S3 - NPV of Net SDM $Benefits /WTG - 10 Yr payback period	$29,250	$76,250	$50,500	$9,500	$37,500	$50,500
	S3 - Annual fee - 5 Yr payback period	$4,250	$20,000	$10,750	$4,000	$5,750	$10,250
	S3 - Annual fee - 7.5 Yr payback period	$4,750	$20,750	$11,500	$4,000	$6,250	$11,000
	S3 - Annual fee - 10 Yr payback period	$5,250	$21,250	$12,000	$4,000	$7,000	$11,500

Table 5-4 (continued)
Summary of Probabilistic Assessment for Scenario 3

	Category	Min.	Max.	Mean	Std Dev.	P90	P50
INPUTS	Discount rate	5.50%	10.00%	7.50%	0.90%	6.30%	7.40%
	Capital cost of SDM Development	$335,000	$455,000	$380,000	$25,000	$345,000	$375,000
	Turbine Capital Cost (/kW)	$1,500	$2,000	$1,750	$100	$1,750	$1,750
	% reduction O&M costs (Yr 1-5)	4.00%	5.50%	4.80%	0.30%	4.40%	4.90%
	% reduction O&M costs (Yr 6-20)	8.00%	11.00%	9.70%	0.60%	8.80%	9.70%
	Power Perf. Improvement	0.30%	3.00%	1.40%	0.80%	0.40%	1.30%

Discussion

Of the three scenarios evaluated, Scenario 1 shows the most potential for reducing COE. The P90 value for the estimated percent change in Cost of Energy is -4.9%. Therefore, in 90% of outcomes the simulation is estimating that CoE will be reduced by at least 4.9% over the life of the project. This is driven primarily by 1) increased revenue due to power performance improvement using SDM to perform power curve analysis followed by 2) reduction in O&M cost from CM. The CoE estimate for Scenario 1 is particularly sensitive to variations in the impact of PPI as shown in Figure 5-7. This tornado graph shows the amount of change in the output (CoE) due to a +1 standard deviation change in each input.

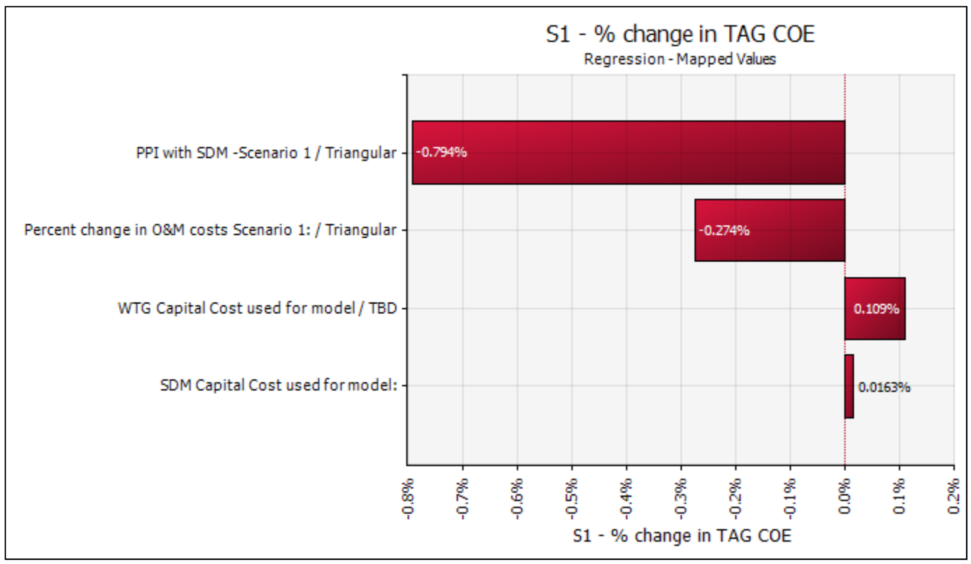


Figure 5-7
CoE Sensitivities to Input Values – Scenario 1

The estimated impact of SDM on the CoE of Scenario 1 is nearly three times that of Scenario 2 and 1.5 times that of Scenario 3. The P90 values for the estimated percent change in CoE are -1.7% for Scenario 2 and -3.3% for Scenario 3. Again, these impacts are most sensitive to changes in the impact of PPI as shown by the tornado graphs below (Figure 5-8 and Figure 5-9).

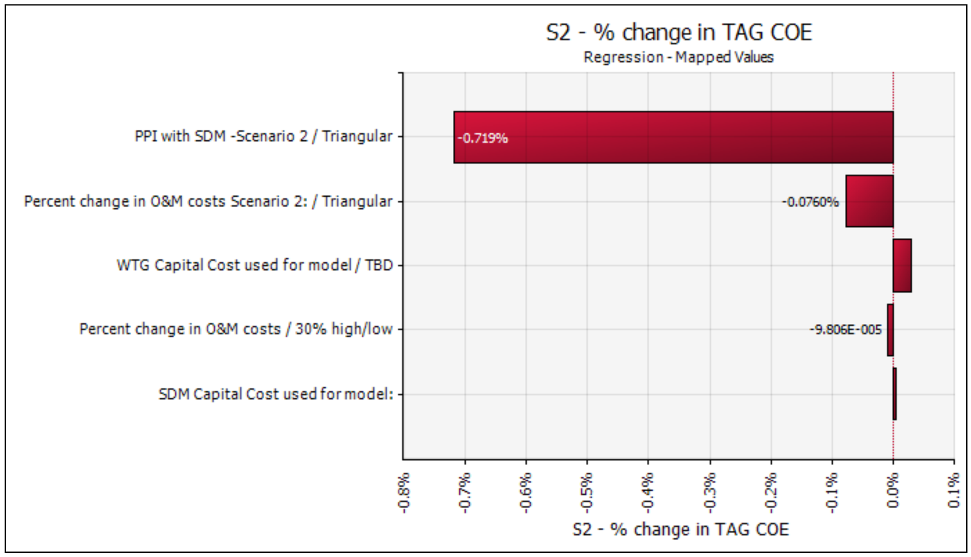


Figure 5-8
CoE Sensitivities to Input Values – Scenario 2

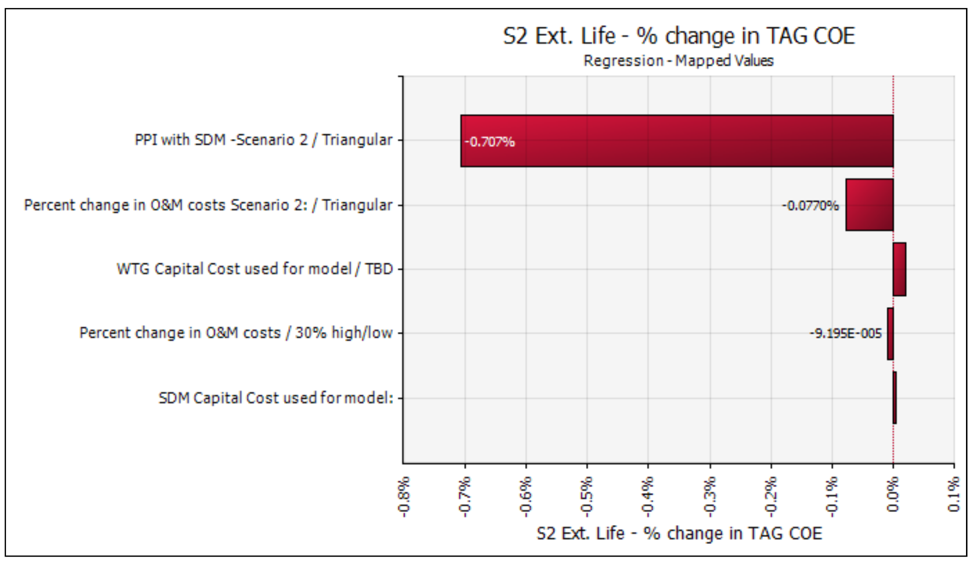


Figure 5-9
CoE Sensitivities to Input Values – Scenario 3

Because of the larger capacity of the turbines in Scenarios 2 and 3, the cash flows are also larger in those scenarios compared to Scenario 1. Therefore, despite a greater impact on CoE, the NPV of the SDM investment for Scenario 1 is lower than for Scenarios 2 and 3. Using this metric, SDM is most valuable for Scenario 3 where the additional revenue assumed in years 21 and 22 of operation contribute to a P90 value for NPV of $50,000 per turbine (assuming a 5 year payback period) compared to $5,250 for S1 and $14,750 for S2.

Conclusions

This report has estimated that an investment in SDM technology appears to have economic merit across all three scenarios evaluated in the study. Although the impacts of SDM may vary from project to project, it is clear that it should be explored as an option for operators trying to achieve high availability and optimal production through the design life of the turbine and beyond.

The value of this technology may be most relevant to projects that no longer have OEM involvement since they are not likely to benefit from OEM driven improvements such as GE's SDA service – offered exclusively as a bundle with their extended service agreements. For these projects, remote CM and performance monitoring could be effectively provided by third-party suppliers of SDM services.

The cost of operating a 24/7 remote monitoring center was estimated to be roughly $1.2MM per year. It is possible to estimate the number of turbines required to fund such an operation. Assuming a 5-year payback period, the range of P90 values estimated for the annual service fee (charged on a per turbine basis) is just under $6,000 for all three scenarios. A remote monitoring center would therefore need at least 200 turbines under contract in order to cover its operational expenses.

All three scenarios considered apply to onshore applications. However, the benefits of reduced component failures would be even greater for offshore wind plants as well as for tall towers because of the higher costs and downtime associated breakdown and the challenges associated with the offshore environment and higher hub heights, respectively.

Recommendations

A number of Research and Development (R&D) activities would further benefit SDM applications to wind turbines. Recommendations for future work include the following.

- The expected benefits of SDM applied in this study are largely based on academic research or limited data from applications of SDM technology by OEMs and third-party developers. An evaluation of this technology would benefit greatly from additional independent testing and operational data.
- Although the initial capital costs of developing machine-specific SDM algorithms for condition-monitoring and performance monitoring may be too much for a single project operating a small number of sub-MW turbines, an owners-groups consisting of several projects operating the same turbine model(as described in Scenario 1) may offer economies of scale that allow for collaborative funding opportunities. An evaluation of this funding model may help accelerate opportunities to bring SDM into the market for older projects operating sub-MW turbines. In this manner, most of the benefits

claimed by large operators with centralized 24/7 manned control rooms can be obtained by smaller operators by collaborating in the development of machine-specific software and funding third party supervisory services.

- The effectiveness of SDM tools will only increase with greater access to higher quality and higher frequency SCADA data. To this end, it is recommended that wind plant owners and operators develop new contract requirement allowing greater access to their wind turbines operational data both during and after the warranty period.
- Standardizing communication protocols across OEM SCADA systems under the IEC 61400-25 standard would significantly improve interoperability and enhance the capacity to link machines of different makes using a single third-party system. Some wind turbine OEMs in the process of developing IEC 61400-25-compliant interfaces to improve the operational management of wind plants with turbines and sensors from various manufacturers. The continued development of IEC-61400-25 compliant systems would greatly benefit the development and capabilities of SDM tools.

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