Data-Driven Wind Turbine Power Generation Performance Assessment Using NI LabVIEW's Watchdog® Agent Toolkit

Lodovico Menozzi, Wenyu Zhao and Edzel Lapira

Abstract Power generation performance is a fundamental metric that all wind farm operators use to determine whether expected power throughput is actually being met. IEC 61400-12-1 has been drafted as an exhaustive power performance measurement scheme for wind turbines. The primary weakness of such a standard is the required level of depth of the associated performance tests, which is more than sufficient for operators to use to run daily wind farm activities. In addition, since this IEC test is not really meant for frequent evaluation, it also fails to capture any loss in power generation performance over time. This paper addresses the aforementioned weaknesses of the IEC standard by the application of data-driven approach to model a wind turbine's power curve. A set of measurements during a known good condition is utilized to setup a baseline model. Regular power curve measurements are then compared while taking into account the multi-regime dynamics of the turbine. The approach was implemented using NI LabVIEW's Watchdog Agent® Toolkit and was successfully validated using actual SCADA data collected from an on-shore wind turbine.

Keywords Wind turbine · Power curve · Multi-regime · Prognostics · Health management

L. Menozzi (✉) · E. Lapira
National Instruments, Italy, Centro Dir.Le Milanofiori Nord, Via Del Bosco Rinnovato, 8 20090 Assago, MI, Italy
e-mail: lodovico.menozzi@uc.com

E. Lapira
e-mail: edzel.lapira@uc.edu

W. Zhao
Center for Intelligent Maintenance Systems at University of Cincinnati, 2600 Clifton Avenue, Cincinnati, OH, USA45221-0072,
e-mail: zhaowy@mail.uc.edu

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1 Introduction

The wind power industry is experiencing capacity installations that continuously increase, engineered by advancements in turbine technologies and surging market needs. According to Global Wind Energy Council (GWEC) 2011 Annual Market Update [1], global wind power capacity increased by 18 % and reached 238 GW. While turbine manufacturing and capacity installation have been the main focus of wind power industry, another key issue that has gradually received considerable attention is wind turbine reliability and maintenance. As U.S. Department of Energy reported [2], Operation and Maintenance (O and M) costs possess over 20 % of total life-cycle cost for offshore wind turbines and 15 % for onshore turbines. To monitor and improve the reliability of wind turbines, development of fundamental research and pioneering technology is required to evaluate turbine power performance, detect faults of critical components and predict failure.

To offer a generic methodology to standardize power performance measurement for different participants of the industry, The International Electrotechnical Commission (IEC) has provided a standard IEC 61400-12-1 [3] as a guideline. Participants, including Original Equipment Manufactures (OEM), wind farm operators, service providers, regulators and academic researchers, have adopted the standard [4]. Although recognized as an accurate and comprehensive method, the IEC standard has the following disadvantages, inherently and observed from practices:

1. To achieve the accuracy advocated by the standard, it requires high data fidelity and inherently expensive monitoring routine. The standard is an exhaustive approach that operators hesitate to perform.
2. The approach and metrics defined in the standard do not generate continuous monitoring value for users, mainly because the cost and time incurred with the measurement. For example, the standard advises 180 h of data for evaluation, which usually takes longer to accumulate enough volume of the data. Therefore, it does not provide a deeper insight of turbine performance deterioration.
3. The method used to calculate energy distribution in wind speed bins and annual energy production (AEP) strongly implies that the projection of wind speed will follow a deterministic distribution, and the turbine will be available and operating at a constant performance level for the next year.

To address the issues above, a data-driven approach is applied to model power curve continuously, which is entailed within a two-tier framework that employs Prognostics and Health Management (PHM) techniques for wind turbine monitoring. Prognostics and Health Management (PHM) is an engineering discipline “focusing on detection, prediction, and management of the health and status of complex engineered systems”, defined by the International Society of PHM and IEEE Society of Reliability. Having been successfully implemented in industries such as rotary machinery, semiconductor manufacturing and aerospace, data-driven PHM has been proposed and developed to ensure continuous and efficient operation of wind energy assets.

In the domain of wind energy, two types of frequently used data are supervisory control and data acquisition (SCADA) data and condition monitoring system (CMS) data. SCADA system is commonly used by operators to monitor turbine parameters and report alarms. It retains sparse measurements including temperature readings, rotation speed and wind speed, which is used to determine daily site activity [5]. In this paper, selected SCADA variables are used to model the deviation of turbine power performance over time.

On the other hand, CMS data is high-resolution sensor data, which may includes vibration, acoustic emission or oil debris analysis data, and used to decide fault indicator for gearbox, generator and bearings [6, 7]. Critical wind turbine components and their reliabilities have been largely surveyed and studied [9–11]. Integrating component downtime distribution and failure probabilities can generate a criticality analysis chart (Fig. 1).

In this chart, quadrant 4 contains components with low failure probability but require longer lead-time for repair when they fail. These components are identified as critical components for turbine system, and are appropriate for opting predictive maintenance strategy and PHM techniques to monitor component health condition much more closely with CMS data.

This paper presents an enhanced framework of wind turbine monitoring and a case study for turbine power performance monitoring. The reminder of the paper is organized as following: Sect. 2 presents the methodology and analytic framework; Sect. 3 introduces how proposed method for wind turbine power performance monitoring is applied to a real-world wind farm; and Sect. 4 summarizes and concludes the work.

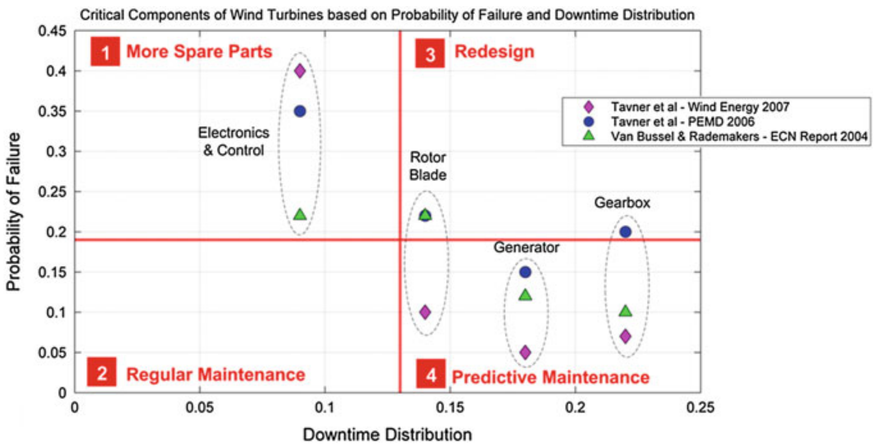

Fig. 1 4-Quadrant criticality analysis for wind turbine components

2 Systematic Methodology

2.1 Overall Framework

A systematic methodology for wind turbine prognostics is proposed and shown in Fig. 2. In this two-tier framework, SCADA data is first used to model turbine overall performance, which is defined as its capability to generate electricity power under varying wind condition. SCADA parameters including output power, wind speed, wind direction and pitch angle are selected to input to a multi-regime model corresponding to turbine's dynamic operating conditions and density function parameters are estimated for each operating regime. In the next step, performance assessment is conducted where current or recent behavior that are represented by the model parameters are compared with normal behavior learned with the same parameters while turbine is known to be new or healthy. A performance indicator frequently generated from the comparison, called Confidence Value (CV) as a Global Health Estimator (GHE) for turbine performance, is then trended over time and predicted with an upper limit R1 and a lower limit R2. The predictions can be converted to forecast when the revenue per unit cycle will drop below a predetermined breakeven level and investigations should be triggered for component Local Damage Estimator (LDE) values.

LDE values are generated from CMS data. Depending on the availability of sensors, the types of data may include vibration, acoustic emission, temperature, and oil debris. Different signal processing tools are used to extract features to

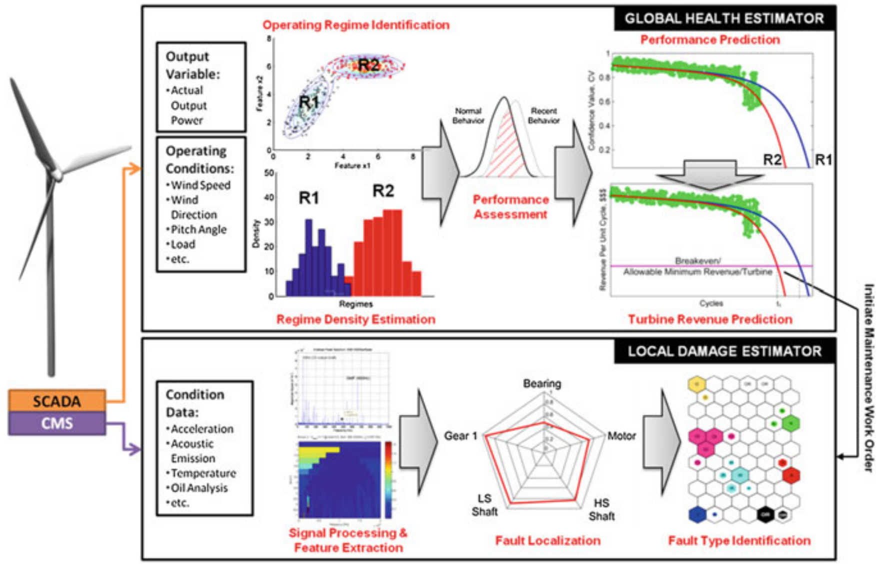

Fig. 2 Systematic methodology for wind turbine prognostics

represent the high-dimension datasets. The features can be used to identify the health degradation status of each instrumented component, and locate component failure that is causing turbine performance reduction. For the located component(s), the specific failure mode can also be identified with diagnosis tools so that correct maintenance action can be suggested.

The proposed framework for wind turbine prognostics can improve existing wind turbine monitoring methods as following:

(1) The highly dynamic environmental condition and operating condition for wind turbines are taken into account with the application of multi-regime modeling method.
(2) Under the framework, various techniques with similar capabilities can be compared and optimized to generate a performance indicator. At the mean time, the indicator is updated frequently and can represent real-time power performance.
(3) A correlation between turbine overall performance and key component defect is investigated, so that the performance metric of CV value can prioritize the effects of degrading components. It allows users to optimize maintenance strategy with a simple yet effective objective.

To aggregate frequently used PHM techniques, the Watchdog Agent® Toolbox is developed as a reconfigurable hardware and software platform for various PHM applications [12]. In National Instruments LabVIEW software, the toolbox includes four categories (as shown in Table 1) of algorithms as Virtual Instruments (VI) for rapid deployment.

The signal processing and feature extraction tools filter, transform and analyze acquired sensor data to extract representative features that are highly related with operation, failure mode or health condition. The feature set then serves as an input to health assessment tools, where pattern recognition and artificial intelligence tools model the similarity between baseline features and features from latest signal, to evaluate overall degradation of the system. Health diagnosis tools, usually

Table 1 Watchdog agent® toolbox algorithms

WATCHDOG AGENT® TOOLS

HEALTH ASSESSMENT		SIGNAL PROCESSING & FEATURE EXTRACTION	
Logistic Regression	Neural Networks	Time Domain Analysis	Wavelet Analysis
Statistical Pattern Recognition	Gaussian Mixture Model	Frequency Domain Analysis	Principal Component Analysis
Self-organizing Maps	Auto-Associative NN	Time-frequency Analysis	Expert Extracted Features
HEALTH DIAGNOSIS		**PERFORMANCE PREDICTION**	
Support Vector Machine	Bayesian Belief Network	Autoregressive Moving Average	Match Matrix
Self-organizing Maps	Hidden Markov Model	Recurrent Neural Network	Trajectory Similarity-based

classification algorithms, can identify the specific impending failure mode at its early stage upon the detection of degradation. Performance prediction tools model the trend of degradation and developing failure mode, to project these indications and estimate the remaining useful life of the system and its components.

For wind turbine PHM, main effort of the estimation of LDE is usually accomplished by selecting suitable tools from numerous algorithms in signal processing category, to extract best features for sensors with different locations and targeted drivetrain components. The computation of GHE, wind turbine's power performance, can be achieved with appropriate health assessment tools.

2.2 Global Health Estimator

To evaluate turbine GHE over time, SCADA data is input to a pre-processing module to be filtered, segmented and normalized. Then parameter selection module determines the relevant variables that will be used to interpret turbine overall performance. As aforementioned that a wind turbine is subjected to dynamic operating conditions, wind turbine data can be represented with as a mixture of distributions through regime partitioning. Several tools can be used here from Watchdog Agent® Toolbox, including Gaussian Mixture Model (GMM), Self-organizing Map (SOM) and Neural Networks. Finally, distance metrics depending on the choice of multi-regime modeling method can be computed to interpret the wind turbine CV through comparing the mixture within similar regime [13] (Fig. 3).

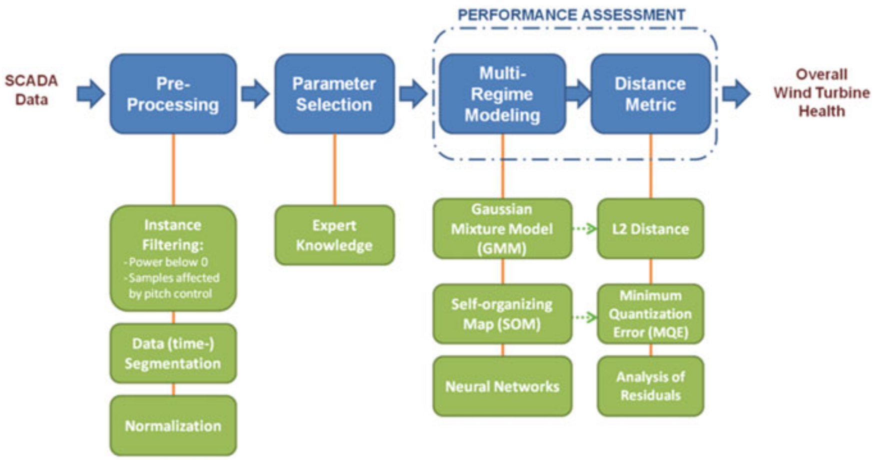

Fig. 3 The overall turbine health represented by GHE

2.3 Local Damage Estimator

Data-driven analytical tools from different categories of Watchdog Agent® Toolbox are employed here to obtain LDE values for each component. For generators, bearings and gearbox, signal processing and feature extraction, feature selection, health assessment and health diagnosis tools can be applied to examine the root cause of turbine degradation and health deterioration at component level [13–15] (Fig. 4).

3 Case Study

A SCADA dataset acquired from an onshore large-scale turbine is used to validate the proposed methodology for estimating GHE. The duration of the data is 26 months, during which SCADA module stores the mean, maximum, minimum and standard deviation of all parameters every 10 min. The actual power output is shown in Fig. 5, where three major downtime events are highlighted in grey shadowed areas: (1) Q1-08–Q20-8, (2) Q1-09–Q3-09 and (3) Q4-09–Q1-10.

Data pre-processing methods are used to reject data instances that will eventually not benefit the analysis. First type is when the actual power is less than zero (when turbine is not generating power), which corresponds to when wind speed is below the wind turbine's cut-in speed. The rest of the wind speed range, even

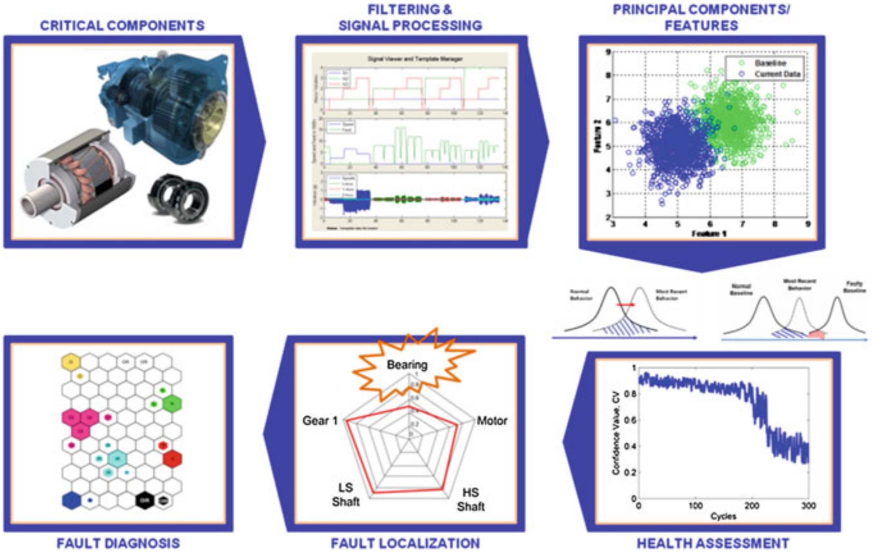

Fig. 4 Systematic approach to estimate LDE for critical turbine components

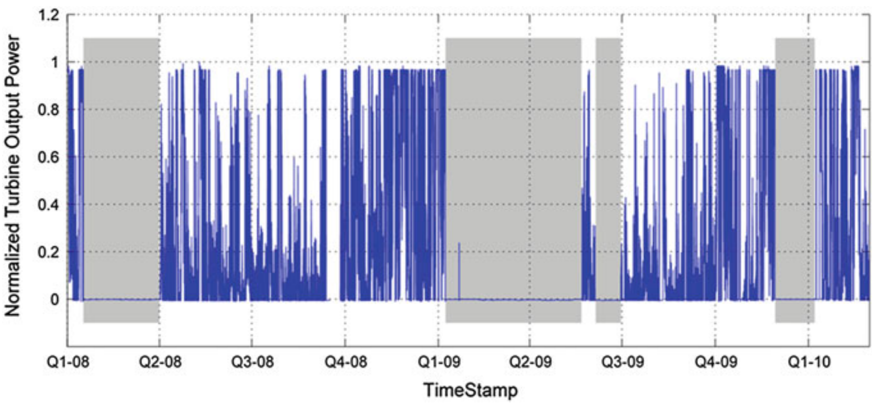

Fig. 5 Actual power generation for the turbine unit

when beyond the turbine's rated cut-out speed, is all kept in this step. Second type of data rejection is based on turbine control mechanism, where power generation is curtailed due to pitch control as counteraction to wind gust rather than turbine's actual degradation. For the wind turbine used in this case study, there is an embedded pitch regulation module designated to adjust the blade's angle of attack with respect to wind direction when high wind speed is observed, so to slow down rotor rotation and limit the drivetrain workload. In the data, power production drops, after high wind speed and rapid change of pitch angle, can be observed. Such instances are rejected to ensure model accuracy.

After pre-processing, wind speed related variables and power output are selected and standardized respectively. All variables are transformed to have zero mean and unity standard deviation. The data is then segmented into 7-day intervals so that the sample size of each segmentation is proper for modeling turbine performance. In this case study, Gaussian Mixture Model (GMM), as shown in Eq. (1), is selected for regime partitioning and health assessment while L2 Distance, as shown in Eq. (2), is selected correspondingly as distance metric to evaluate health degradation.

$$H(x) = \sum_{i=1}^{n} p_i h(x; \theta_i) \tag{1}$$

$$CV = \frac{\|H(x) \cdot G(x)\|_{L2}}{\|H(x)\|_{L2} \cdot \|G(x)\|_{L2}} \tag{2}$$

The number of mixture Gaussian components, n, is first selected to represent the distribution of selected parameters. Then the baseline turbine performance is modeled with the data during first three time intervals where turbine status is assumed to be healthy. For each of the rest intervals, an equivalent Gaussian mixture representation is found and CV is computed using L2 distance between baseline and each of the representation [13]. The trend of CV over time shows that the technique captures the gradual degradation of the turbine unit. With appropriate selection and configuration of a prediction algorithm, providing early alarms of ongoing deterioration could prevent major downtime before it happens.

The implementation of the approach in LabVIEW is shown in Fig. 6 through Fig. 7.

As the process of configuring model training is shown in Fig. 6, pre-processed SCADA data variables, including wind speed, power output and their timestamp, are loaded in step 1 and step 2. Step 3 is where the GMM parameters for training a baseline model are configured, including baseline duration, number of clusters and number of iterations. While model training is triggered, the normalized baseline power curve is displayed to provide an evident observation.

Performance evaluation through testing of the GMM model obtained from remaining data is shown in Fig. 8. As continuation from baseline modeling, step 5 is for configuring GMM parameters for testing and step 6 initiates the calculation of CV value based on the configured parameters. Once testing is completed, CV is shown over time on the right hand side of the panel.

Eventually, the progression of turbine unit power performance, shown as CV, together with wind speed and power output is visualized for user (Fig. 9). Furthermore, a scalable monitoring platform for an entire fleet can be constructed by executing a configured and validated algorithm for each individual turbine.

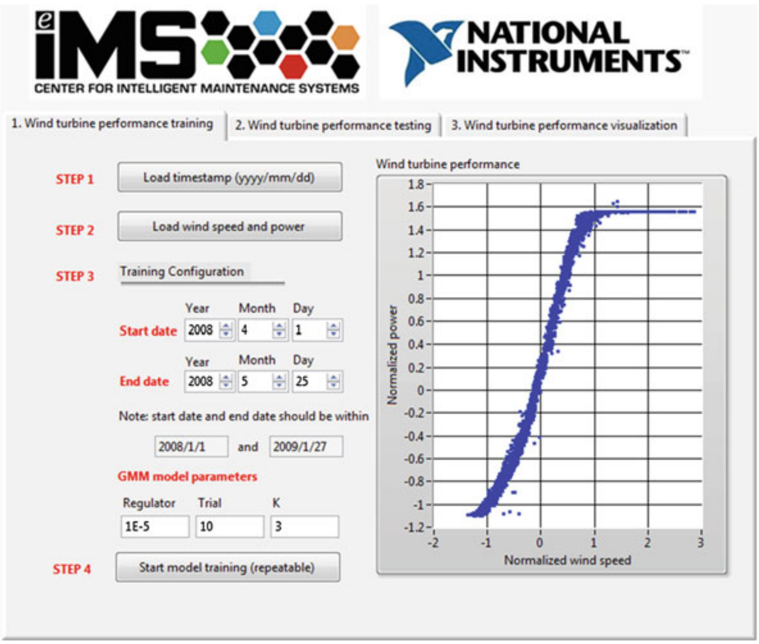

Fig. 6 Configuration of power performance model training with GMM

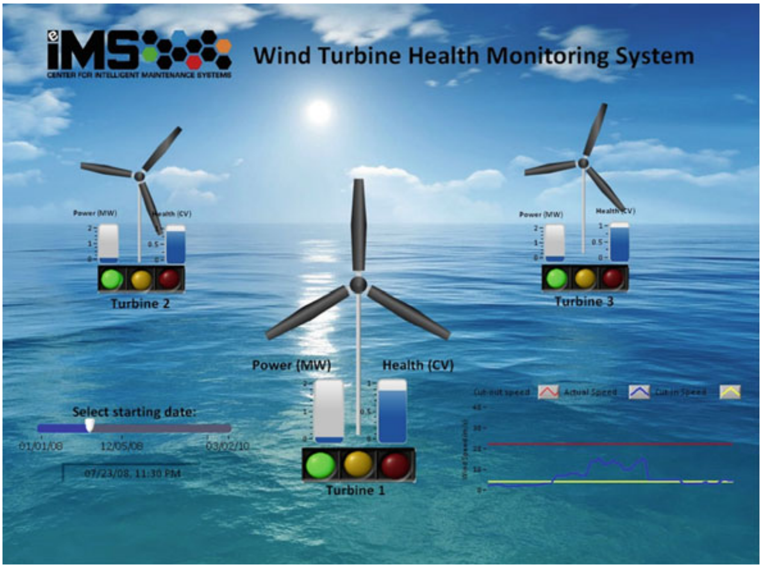

Fig. 7 Demonstration of wind turbine health monitoring system using national instruments LabVIEW [14]

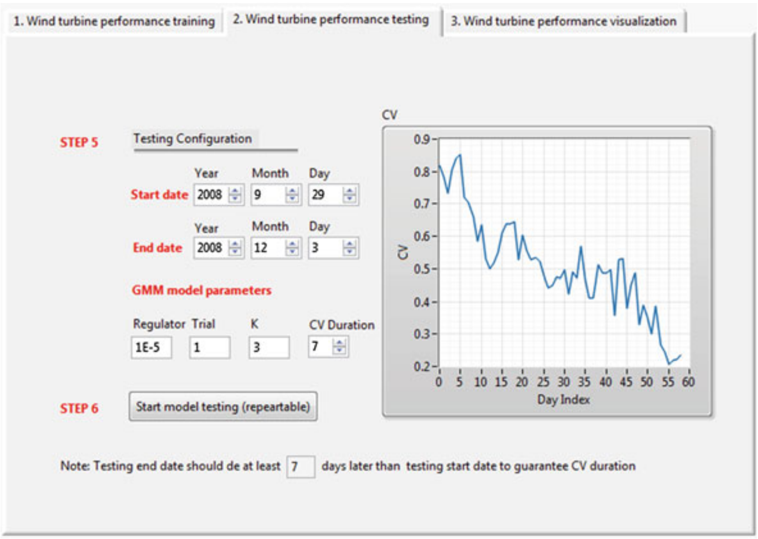

Fig. 8 Configuration of power performance model testing with GMM

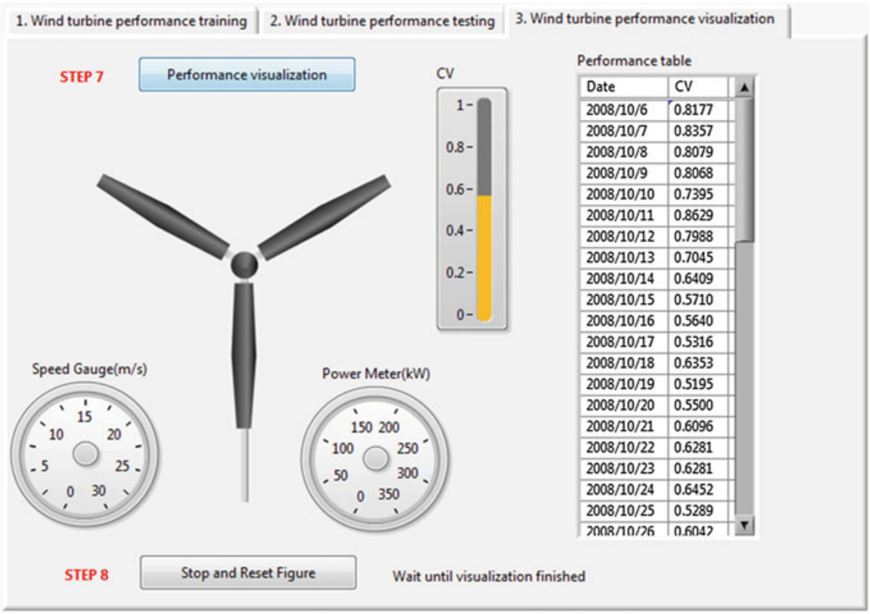

Fig. 9 Visualization of wind turbine power performance

4 Conclusion

This paper presents an advanced framework for wind turbine prognostics and health management. A Global Health Estimator is proposed to enhance current performance testing practices advised by an IEC standard. It is generated with SCADA data to indicate and predict turbine unit overall performance. A Local Damage Estimator is computed to evaluate degradation status of critical turbine drivetrain components, and locate the fault that is the root cause of turbine performance degradation. A case study is presented where Gaussian Mixture Model and L2 Distance are used to compute the GHE. The implementation of GHE computation is presented with Watchdog Toolbox® in National Instruments LabVIEW.

The presented work benefits the wind power industry, as it helps to establish an effective and systematic PHM solution that is capable of dealing with turbines' constantly changing operating conditions and provides predictive maintenance suggestions for wind farm operator. The calculation of GHE utilizes existing SCADA system, provides progressive evaluation of actual power performance and offers opportunities to predict turbine downtime.

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